Patterns Identification of Finger Outer Knuckles by Utilizing Local Directional Number

Original Scientific Paper

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Abstract – *Finger Outer Knuckle (FOK) is a distinctive biometric that has grown in popularity recently. This results from its inborn qualities such as stability, protection, and specific anatomical patterns. Applications for the identification of FOK patterns include forensic investigations, access control systems, and personal identity. In this study, we suggest a method for identifying FOK patterns using Local Directional Number (LDN) codes produced from gradient-based compass masks. For the FOK pattern matching, the suggested method uses two asymmetric masks—Kirsch and Gaussian derivative—to compute the edge response and extract LDN codes. To calculate edge response on the pattern, an asymmetric compass mask made from the Gaussian derivative mask is created by rotating the Kirsch mask by 45 degrees to provide edge response in eight distinct directions. The edge response of each mask and the combination of dominating vector numbers are examined during the LDN code-generating process. A distance metric can be used to compare the LDN code's condensed representation of the FOK pattern to the original for matching purposes. On the Indian Institute of Technology Delhi Finger Knuckle (IITDFK) database, the efficiency of the suggested procedure is assessed. The data show that the suggested strategy is effective, with an Equal Error Rate (EER) of 10.78%. This value performs better than other EER values when compared to different approaches.*

Keywords: *Finger Outer Knuckles, Local Directional Number, Pattern Identification, Image Processing*

1. INTRODUCTION

Access control and proper personal identification technologies are necessary to create safe and efficient systems. Each person's internal and external physiological biometrics have several characteristics in common. With imaging technology, even in a touchless manner, they are more practical and simple to use. Because of the intricate architecture of the human hand, remarkable recognition abilities can be found on the dorsal surface of the fingers. [1]. Finger Outer Knuckles (FOK) have a distinctive pattern formation that makes it a promising biometric identifier for advancements in personal identification because it is both pleasant and touchless [2]. The asymmetry of the finger is caused by the anatomy's capacity for forward bending and resistance to backward movement, which causes many wrinkles on the palm.

Metacarpophalangeal joints, commonly referred to as finger outer knuckles, are important joints that attach the fingers to the hand's bones. The shape of the knuckles is important for dexterity, grip strength, and hand movements. Due to their distinctive patterns, there has been an increase in interest in employing finger outer knuckles for biometric authentication in recent years [3, 4]. However, their complicated and uneven structure makes finger outer knuckles difficult to find patterns in. Thankfully, new developments in machine learning and image processing methods have made it possible to evaluate these patterns precisely.

One such method involves identifying and categorizing the patterns in the finger's outer knuckles using local directional numbers (LDNs). LDNs are mathematical descriptors that quantify the gradient orientation at each pixel in an image. In numerous computer vision applications, such as texture analysis and object recognition, they successfully measure the local directional information in an image [5, 6]. Researchers can employ LDNs to extract directional information from patterns on finger outer knuckles and classify such patterns into various groups.

There are numerous issues that need to be resolved because using LDNs to determine finger outer knuckle patterns is still a relatively new technology. For joint fingerprinting, central joint line extraction, for instance, is a considerable challenge, necessitating the implementation of dependable components in addition to the knuckle print matching technique [7, 8].

There are numerous possible uses for identifying finger outer knuckle patterns utilizing LDNs. It might be utilized, for instance, in biometric authentication systems, where the patterns could act as distinctive personal IDs for people. Additionally, it could be applied to medical imaging to detect disorders that affect the finger joints or injuries to the hands [9, 10].

Utilizing the LDN to FOKs for identification is the paper's goal and main contribution. We intend to open up a new arena for the problem of identifying people by employing this method.

This paper is structured as follows: Section 1 presents the introduction, Section 2 reviews prior studies, Section 3 explains the proposed approach, Section 4 discusses obtained results and Section 5 provides the conclusion.

2. FOK LITERATURE REVIEW

To correctly recognize finger outer knuckle (FOK) patterns, portions of the finger or hand must be segmented. False positives or false negatives may come from misidentification caused by improper segmentation [11]. The process of segmentation involves separating regions or important objects from an image or data set. Finding the finger or hand joint regions that contain the FOK patterns requires precise segmentation [12].

The clarity of the segmentation can be affected by several variables, such as the intricacy of the hand or finger structure, lighting circumstances, and image quality. To increase segmentation accuracy, researchers have created a variety of methodologies, including deep learning-based approaches and morphological procedures [13]. Furthermore, using various imaging techniques like magnetic resonance imaging (MRI) and ultrasound can provide more thorough details on the structure of the hand or finger, which can help with precise segmentation and FOK pattern identification [14, 15].

FOK patterns are built on lines easily retrieved using a low-cost sensor, making them a promising biometric modality. FOKs are a feasible alternative to other biometric modalities like fingerprints because they are naturally protected and less likely to change due to aging or injury [16]. Finding FOK patterns, meanwhile, comes with its own set of difficulties. The FOK patterns may appear differently in each image due to rotations and translations, which makes it more difficult to match them precisely. Illumination contrast can also lead to poor image quality [17, 18].

Typically, the FOK imprint is made up of two parallel lines joined by smaller lines to create a unique design. This pattern can be extracted by a number of sensors, including contact-based sensors, capacitive sensors, and optical sensors [19]. Different directions of the FOK have rich pattern structure lines, however, they are severely discriminated against. When compared to fingerprints, the failure rates of FOK patterns are anticipated to be lower as these lines tend to fade with age [20, 21].

Calculating the number of focus edges, the amount of clutter, the focus edge distribution, the entropy sensible of the focused advantages, the reflection caused by the light source or camera flash, and the quantity of contrast can increase the quality of the knuckle print image. To ensure durability against changing illumination, features based on vertical and horizontal joint lines may be of poor quality and require refinement and conversion [22, 23].

3. PROPOSED APPROACH

3.1. DESCRIPTION

The suggested method entails examining the structural data and density variations in the tissue of the outer finger joints using image processing methods. The local area structure of the FOK is encrypted by the LDN algorithm, which then examines the data it contains. The edge responses are then calculated using a compass mask in eight different orientations. As demonstrated in Fig. 1, a relevant descriptor for the tissue's structural pattern is generated by choosing the highest positive and negative trends. This method enables the separation between texture intensity variations, such as those from bright to dark and vice versa, which can aid in differentiating between related patterns.

The suggested method has several benefits over conventional fingerprinting methods. It can be utilized when standard fingerprinting isn't an option, as when the skin is severely injured or calloused. Furthermore, LDN analysis can offer a higher level of precision when identifying people based on their FOKs. Instead of using isolated calculated points, the complete information area is utilised, and the data is converted to a six-bit code. The encoded information is expanded by applying various masks and resolutions on the mask to gain properties that a single mask could overlook. Multiple encoding levels have been shown to enhance the detecting process.

It is essential to use all available information for precise pattern recognition while studying Finger Outer Knuckles (FOKs) utilizing Local Directional Number (LDN) approaches. To do this, a six-bit code based on the structural patterns and density variations in the imaged tissue of the FOK is formed, and various masks and resolutions are applied to the mask to obtain more information. The detecting method is further enhanced by having various encoding levels since different codes can be merged to produce a more precise representation of the FOK pattern.

The direction of the gradient between bright and dark areas is revealed by the positive and negative computations in LDN, which offers important information on tissue architecture.

The ability of LDN to distinguish between blocks while reversing the positive and negative axes is crucial for correctly identifying specific texture modifications. These transformations are given a specific code by LDN, ensuring that they are appropriately distinguished.

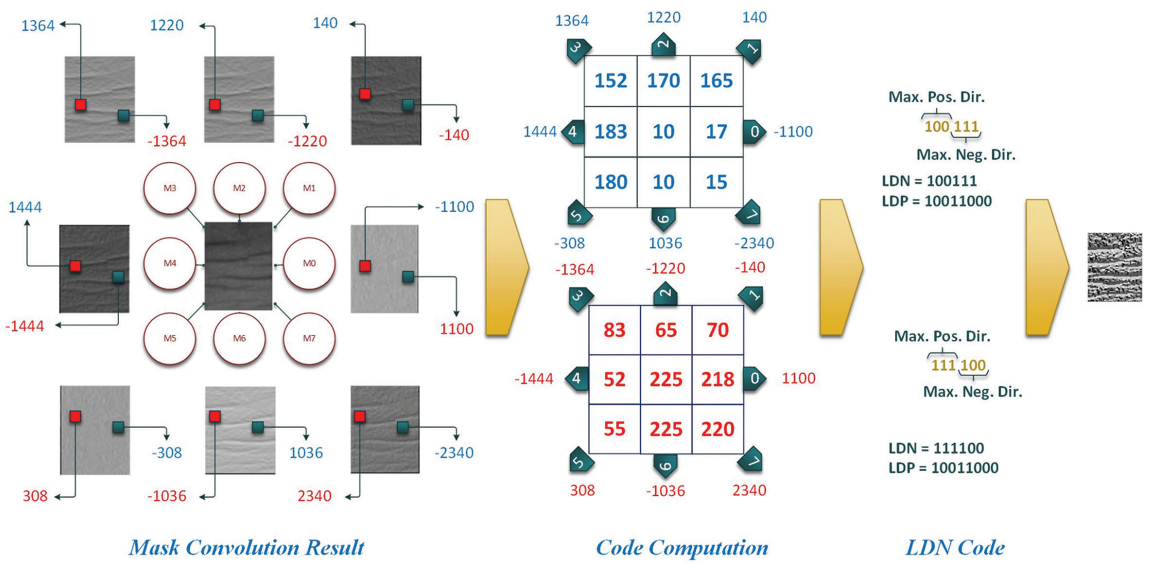

Fig. 1. Demonstration of computing the LDN code

In comparison to conventional fingerprinting methods, the suggested LDN method offers a more thorough and effective means of recognizing patterns of finger outer knuckles. The LDN method can offer improved precision, resolution, and sensitivity to changes in texture and lighting conditions by making use of the complete information region of the FOK, applying several masks with varying resolutions, and adopting a more reliable and effective encoding scheme.

Additionally, the LDN algorithm outperforms conventional texture analysis methods since it is largely insensitive to variations in lighting. Further expanding the encoded information and enhancing the detection process are the use of several encoding levels and the application of various masks with various resolutions.

By examining edge responses in eight distinct directions and utilizing two different masks—Gaussian-derivative and Kirsch's compass mask—the LDN algorithm can give more resolution and sensitivity to changes in texture and lighting conditions than the Local Binary Pattern (LBP) technique. The LDN algorithm also filters and prioritizes local information prior to coding, minimizing the effects of low resolution and noise sensitivity.

The suggested method for recognizing patterns of finger outer knuckles using local directional number (LDN) has several advantages over conventional fingerprinting approaches, including greater accuracy, resolution, and sensitivity to changes in texture and lighting conditions. The LDN algorithm can extract more meaningful patterns from the input image by using a more thorough approach that considers the input image's information and applying multiple masks with various resolutions, making it a more robust and successful method for pattern identification of finger outer knuckles.

The proposed work (as in Fig. 2) can be summarized through the following algorithm:

1. Obtain a dataset of images of the Finger Outer Knuckles (FOK) for testing and training the algorithm, and then increase contrast and eliminate noise from the photos.
2. Employ the suggested technique to extract Local Directional Number (LDN) codes from the preprocessed images. The directional information can be extracted from the FOK patterns using the LDN codes, which quantify the gradient orientation at each pixel in the image. The following steps can be used to calculate the LDN codes:
   a. Blocks of a specified size, with no overlap, should be created from the preprocessed image.
   b. Use a filter to calculate the gradient's strength and direction at each pixel in each block.
   c. Quantize the gradient direction into a set of bins of a certain size, such 8 or 16.

d. Concatenate the quantized gradient orientations of each pixel's surrounding pixels in a circular pattern to determine the LDN code for each pixel in each block.

3. Determine the model's Equal Error Rate (EER), a widely used parameter in biometric identification. The False Acceptance Rate (FAR) and False Rejection Rate (FRR) are identical at the EER. The FRR is the likelihood of rejecting a legitimate user as an impostor, while the FAR is the likelihood of accepting an impostor as a genuine user.
4. Examine the findings and contrast the suggested method's EER with those of other FOK pattern recognition techniques already in use. The objective is to demonstrate that the proposed technique outperforms or performs on par with competing methods in terms of accuracy and resilience.
5. To attain the lowest EER feasible, optimize the proposed method's parameters, such as the sigma value. The sigma value affects the method's ability to discriminate between different data sets by regulating the size of the Gaussian kernel used to smooth the LDN codes. A grid search or a random search over a range of sigma values can be used to perform the optimization.
6. Repeat steps 2 through 5 until the suggested technique performs admirably on the test dataset.

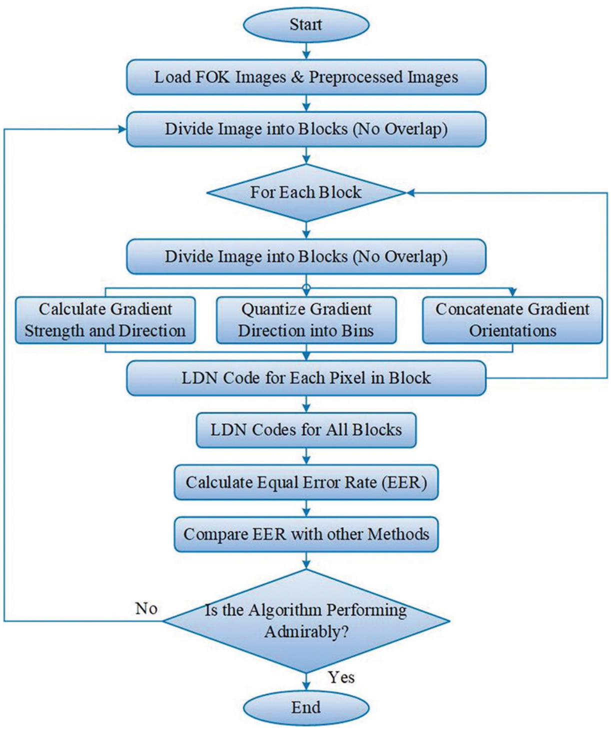

Fig. 2. General Flowchart for Research Method

3.2. CODING SCHEME

In the suggested work, LDN codes are created by analyzing each mask's edge response ($M0$,..., $M7$) and the combination of dominating vector numbers. An use of feature descriptors called LDN codes is in image analysis and computer vision. Each mask's edge response identifies any salient dark or bright areas in the image, and the signal data is then implicitly used to encode these regions. The three most significant bits in the code reflect the highest positive directional number, which is given a fixed position in the code [24]. The largest negative directional number is represented by the three least significant bits, as seen in Fig. 1. The following is a definition of the key LDN equation:

$$LDN(x,y) = 8i_{x,y} + j_{x,y} \tag{1}$$

where (x, y) is the center pixel of the region being coded, $i_{x,y}$ is the vector number of the maximum positive response, and $j_{x,y}$ is the vector number of the minimum negative response specified by:

$$\begin{aligned} i_{x,y} &= \arg\max_i \{\mathbb{I}^i(x,y) \mid 0 \le i \le 7\}, \\ j_{x,y} &= \arg\min_j \{\mathbb{I}^j(x,y) \mid 0 \le j \le 7\}, \end{aligned} \tag{2}$$

where $\mathbb{I}^i$ is the convolution of the original image I for the i^{th} mask, M^i is defined by:

$$\mathbb{I}^i = I * M^i \tag{3}$$

3.3. COMPASS MASKS

Compass masks are a sort of filter used in image processing for edge detection and feature extraction. These masks are used in the planned work for FOK pattern matching and identification. One of the main benefits of employing compass masks is that the LDN code is computed using the gradient area rather than the density feature area. Because it implicitly carries the relationships between pixels in the image, the gradient area has more information than the density feature area. This makes it possible to describe the image structure more accurately and identify important tissue features more effectively [25].

In order to increase the stability of the gradient computation, Gaussian smoothing is additionally applied to the image before gradient calculation. Gaussian smoothing optimizes the accuracy of the LDN code calculation by lowering image noise and enhancing image clarity. The proposed method is strengthened and made more trustworthy for matching and identifying FOK patterns as a result of these procedures. Even in the face of noise and other image abnormalities, the employment of compass masks and Gaussian smoothing enables a more accurate depiction of the image structure and a more effective identification of significant tissue characteristics.

A compass mask must be supplied to compute the image's edge responses and generate the LDN code. Two asymmetric masks—Kirsch and Gaussian derivative masks—were examined for FOK pattern detection in the research that was proposed. Compass masks, such as Kirsch masks, comprise eight distinct 3x3 kernels. The edge response is determined by the convolution of the kernel with the image, with each kernel being orientated differently. The Kirsch mask is a flexible option for edge detection in image processing since it can identify edges in all directions.

On the other hand, the Gaussian derivative mask is a sort of filter that determines the edge response using the gradient space of the picture. In order to stabilize the code in the presence of noise, it additionally employs Gaussian smoothing. Gaussian smoothing optimizes the accuracy of the LDN code calculation by lowering image noise and enhancing image clarity.

Both masks work in the image's gradient space, which displays the image's fundamental structure and improves the method's discrimination when identifying relevant tissue characteristics. The LDN code calculation's stability is further enhanced by using Gaussian smoothing, which increases the method's resistance to noise and other image distortions. To acquire the edge response in eight different directions, the Kirsch mask employed in the proposed work is rotated 45 degrees from the horizontal and vertical directions, as illustrated in Fig. 1. The Kirsch mask inspired the LDNK method, which is used to identify FOK patterns using this mask.

The suggested technique uses the Kirsch mask and an oblique Gaussian derivative mask to produce an asymmetric compass mask for computing the edge response on texturing. This mask is intended to produce strong edge responses while resisting noise and brightness variations.

A Gaussian function is convolved with the derivative of the picture to produce the Gaussian derivative mask that is employed in the proposed work. The standard deviation, which establishes how much smoothing is applied to the image, defines the Gaussian function. The derivative is computed in a certain direction, which shows the mask's orientation. Gaussian mask selection is based on:

$$\begin{aligned} G_\sigma(x,y) &= \frac{1}{2\pi\sigma^2}\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \\ M_\sigma(x,y) &= G'_\sigma(x+k,y) * G_\sigma(x,y) \end{aligned} \tag{4}$$

where σ is the width of the Gaussian bell, G is the derivative of G_σ concerning x, $*$ is the convolution process and k is the Gaussian displacement concerning its center as a quarter of the mask diameter used for this displacement. Next, an $\{M_{0\sigma}$ compass mask is created. . ., $M_{7\sigma}\}$ alternating M_σ, 45 each separately in eight different directions. Thus, a set of masks similar to that shown in Fig. 1 is obtained. Because M_σ rotates the mask, there is no need to compute the derivative concerning y (since it is equivalent to 90 degrees rotating mask) or some other combination of these variables.

4. RESULTS AND DISCUSSIONS

4.1. EMPLOYED DATABASE

The Indian Institute of Technology Delhi Finger Knuckle (IITDFK) database was used in this investigation [26]. This database includes 500 segmented pictures of 100 subjects' finger outer knuckle (FOK) patterns. There are five grayscale photos of each subject, each with an 80x100 pixel resolution.

The subjects for the photographs in the IITDFK database placed their fingers on a level surface with a black background, and the photographs were taken with a typical digital camera under controlled lighting settings. The subjects were standing about 30 cm away from the camera when the pictures were taken.

Several earlier studies on identifying and recognizing FOK patterns utilized the IITDFK database. It has been extensively used to assess the efficacy of several methods for identifying FOK patterns, such as texture analysis, feature extraction, and machine learning techniques [26].

A standardized database, like the IITDFK database, can compare and evaluate various methods for consistently identifying FOK patterns. It also makes it easier to create and refine FOK pattern recognition systems for a variety of practical uses, such as forensic analysis, access control, and personal identity.

4.2. RESULTS

On the Indian Institute of Technology Delhi Finger Knuckle (IITDFK) database, the proposed method for FOK pattern recognition utilizing Local Directional Number (LDN) codes produced from gradient-based compass masks was assessed. The database includes 100 participants' left and right index, middle, and ring fingers in nine photographs for each of the collection's 500 images of FOK patterns.

The LDN codes were created for each image in the database using Kirsch and Gaussian derivative masks in order to assess the effectiveness of the suggested method. The LDN codes of each pair of photos were then compared using a distance metric, and the results were examined. In this investigation, 100 participants were taken into account. As said, there are 5 photos for each theme. These result in 123750 attempts for impostor comparisons and 1000 attempts for real comparisons during identification.

First of all, experiments are implemented by using the Matlab software (version R2020a) and a computer with the following hardware specifications: hp laptop, Intel core i7 processor, 2.70GHz processor speed and 8GB Random Access Memory (RAM). The performance of the approach is assessed using the Equal Error Rate (EER), which is one of the most considered essential metrics in biometrics. Its lower numbers indicate greater performance and vice versa. The outcomes show that the suggested approach identified FOK patterns successfully with an EER of 10.78%. It can be seen that the proposed technique outperforms the other ways by contrasting the EER values of the two methods. This shows that the suggested strategy is more accurate and effective for identifying FOK patterns. The table also demonstrates that altering the sigma value significantly affects the EER, with the lowest EER being attained at a sigma value of 0.85. This shows that choosing the right sigma value is essential for using the proposed method to identify FOK patterns with high accuracy.

The suggested method's low loss rates show that LDN codes created using gradient-based compass masks are a dependable and effective for identifying FOK patterns. The FOK pattern is uniquely represented by the asymmetric Kirsch and Gaussian derivative masks used to create the LDN codes, enabling accurate matching even in the presence of noise and distortion.

The proposed approach is suited for usage in various real-world settings, including forensic investigations, access control systems, and personal identification, according to the low loss rates obtained for each finger. However, the right ring finger's somewhat greater loss rate suggests that additional research may be required to optimize the strategy for this finger.

4.3. DISCUSSIONS

We conducted experiments using various mask sizes while maintaining the default values of mask type ('kirsch') and sigma value (0.5) to assess the impact of modifying the mask size on identification outcomes. The identification outcomes for varying the mask size when using the standard mask type of "kirsch" and a sigma value of 0.5 are shown in Table 1. EER, a popular statistic used in biometric identification to assess a system's performance, is used to measure the outcomes.

Table 1. Identification results for changing the mask size and using the default values of mask = 'kirsch' and sigma = 0.5

Ind.	Mask Size	EER (%)	Accuracy (%)
1	3x3	15.09	84.91
2	5x5	12.52	87.48
3	7x7	11.92	88.08
4	9x9	11.71	88.29
5	11x11*	12.91	87.09

* a problem with sizing appeared, so, it has been solved by resizing.

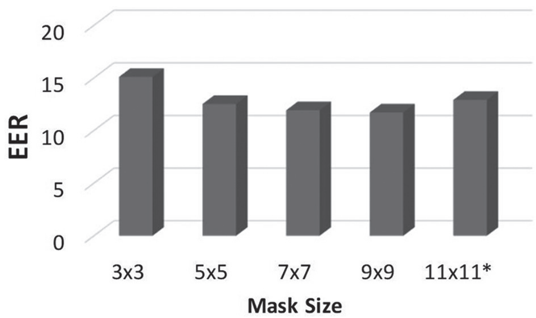

Fig. 3. bar chart to identify results for changing the mask size

AS INDICATED IN THE TABLE, the EER reduces with increasing mask size, with a mask size of 99 producing the lowest EER of 11.71%. This implies that increasing the mask size can increase the FOK pattern identification method's accuracy when employing LDN codes.

The results do, however, also suggest that there is a limit beyond which raising the mask size can reduce the system's performance. For instance, a resizing issue occurred when a mask size of 1111 was employed, leading to a higher EER of 12.91%.

When employing the LDN code technique for identifying FOK patterns, the findings in this table emphasize how crucial it is to choose the right mask size carefully. High levels of accuracy and improved system performance can be obtained by selecting a suitable mask size.

Table 2. Identification results for changing the mask type and using the values of mask size = 9x9 and sigma = 0.5

Ind.	Mask Type	EER (%)	Accuracy (%)
1	Prewitt	13.98	86.02
2	Sobel	13.21	86.79
3	Kirsch	11.71	88.29
4	Gaussian	11.50	88.5

With a fixed mask size of 99 and a sigma value of 0.5, Table 2 shows the identification results for varying the mask type. EER, a popular metric for assessing system performance in biometric identification, is used to measure the outcomes.

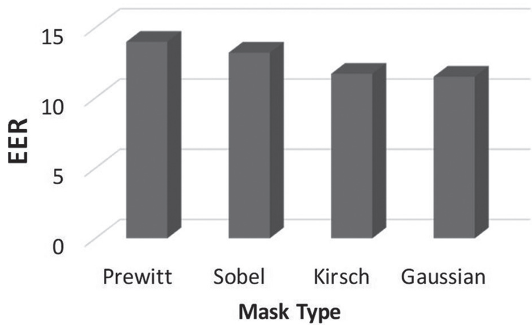

Fig. 4. bar chart to identify results for changing the mask type

With an EER of 11.50%, the table shown demonstrates that the FOK pattern identification strategy employing LDN codes performs best when using the Gaussian mask type. With an EER of 11.71, the Kirsch mask type also performs well. Prewitt and Sobel masks, on the other hand, had greater EERs, at 13.98% and 13.21%, respectively.

These findings emphasize the significance of choosing the proper mask type when employing the LDN code technique for identifying FOK patterns, as the choice of mask type can significantly affect the system's performance. The dataset in this scenario responds best to the Gaussian mask type, closely followed by the Kirsch mask type. It is crucial to keep in mind, nevertheless, that the ideal mask type could change based on the application in question and the features of the FOK patterns being examined.

It is significant to note that the Gaussian mask type has no impact on the values of mask size. The parameter that is impacted in this scenario is the sigma value. To identify the ideal sigma value for the Gaussian mask type, more tests must be done.

The identification outcomes for varying the sigma value while utilizing the Gaussian mask type, with the EER as the generally employed performance metric in biometric identification, are shown in Table 3.

The EER first drops as the sigma value rises, reaching a minimum value, as indicated in the table. After that, the EER increases once more as the sigma value grows. This dataset's ideal sigma value appears to be 0.85, which produced the lowest EER of 10.78%.

The EERs shown in this table are often greater than the accuracy numbers reported in the previous tables, which is important to note. This is so because accuracy simply considers the quantity of correctly identified patterns, whereas EER also considers incorrect acceptance and false rejection rates.

Table 3. Identification results for changing the sigma value and using the mask type of Gaussian

Ind.	Sigma Value	EER (%)	Accuracy (%)
1	0.05	15.36	84.64
2	0.10	15.36	84.64
3	0.15	15.22	84.78
4	0.20	15.50	84.5
5	0.25	15.20	84.8
6	0.30	15.02	84.98
7	0.35	11.89	88.11
8	0.40	11.83	88.17
9	0.45	11.66	88.34
10	0.50	11.50	88.5
11	0.55	11.63	88.37
12	0.60	11.69	88.31
13	0.65	11.25	88.75
14	0.70	11.51	88.49
15	0.75	10.99	89.01
16	0.80	10.88	89.12
17	0.85	10.78	10.78
18	0.90	10.89	89.11
19	0.95	11.04	88.96
20	1.00	11.42	88.58

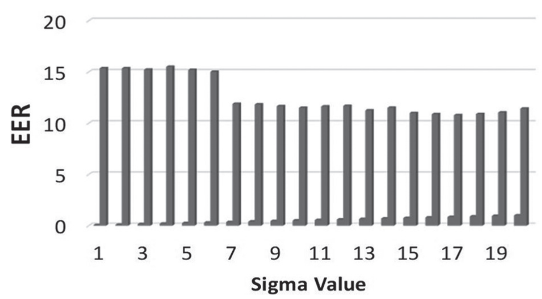

Fig. 5. Bar chart to identification results for changing the sigma value and using the mask type of Gaussian

These findings imply that selecting a sigma value can significantly influence the effectiveness of the FOK pattern detection approach employing LDN codes. In this instance, a sigma value of 0.85 seems to work well for this dataset. However as was already established, the ideal sigma value may change based on the particular application and the properties of the FOK patterns being examined.

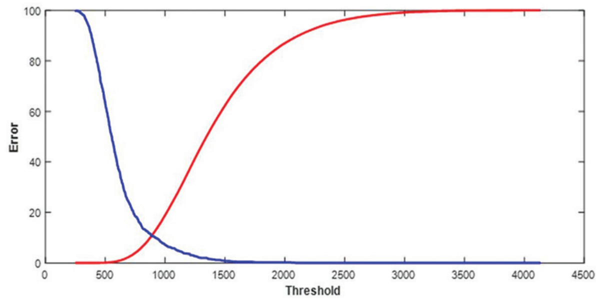

Fig. 6. FAR versus FRR for the proposed identification

The suggested FOK pattern detection method's False Accept Rate (FAR) against False Reject Rate (FRR) is plotted in Fig. 6. The error rate is shown on the x-axis, while the threshold is on the y-axis. As the plot shows, a decreasing FAR corresponds to an increasing FRR, and vice versa, which illustrates a trade-off between the FAR and FRR. The plot can be used to choose the best threshold for a particular application and aids in visualizing how well the suggested strategy performs at various threshold values.

A Receiver Operating Characteristic (ROC) curve plot of the suggested FOK pattern identification method's performance is shown in Fig. 7. Genuine Attempts Accepted (1-FRR) is shown on the x-axis, and Impostor Attempts Accepted (1-FAR) is. The True Positive Rate (TPR) against False Positive Rate (FPR) at various threshold settings is plotted on the ROC curve. As the curve shows, a greater TPR leads to a higher FPR, which illustrates a trade-off between the two metrics. The overall performance of the approach is measured by the Area Under the Curve (AUC) of ROC, with a greater AUC indicating better performance. The ROC curve and AUC can be used to compare the effectiveness of various biometric identification techniques and to establish the ideal operating point for a particular application.

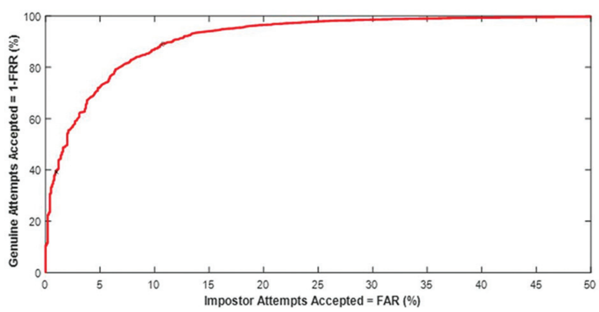

Fig. 7. ROC curve for the proposed identification

An illustration of the correlation between the false reject rate (FRR) and false acceptance rate (FAR) is called a detection error trade-off (DET) curve. The x-axis shows the FRR and the FAR is represented by the y-axis. Fig. 8 illustrates how the DET curve is often shown on a log scale to better easily visualize subtle variations in error rates.

When the cost of a false rejection is greater than that of a false acceptance, the DET curve helps assess the performance of biometric systems. A decision threshold must be selected in these systems to balance the FRR and FAR trade-off. This trade-off is visualized by the DET curve, which also enables the appropriate decision threshold to be chosen based on the intended operating point. A successful system should have a curve that is as close as feasible to the bottom left corner of the graph to indicate low error rates for both erroneous acceptances and false rejections. The outcomes of a FOK and LDN with carefully selected parameters are shown in Fig. 9.

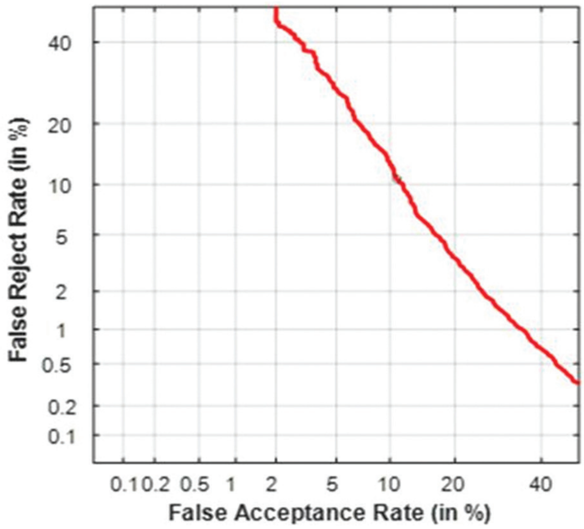

Fig. 8. DET curve for the proposed identification

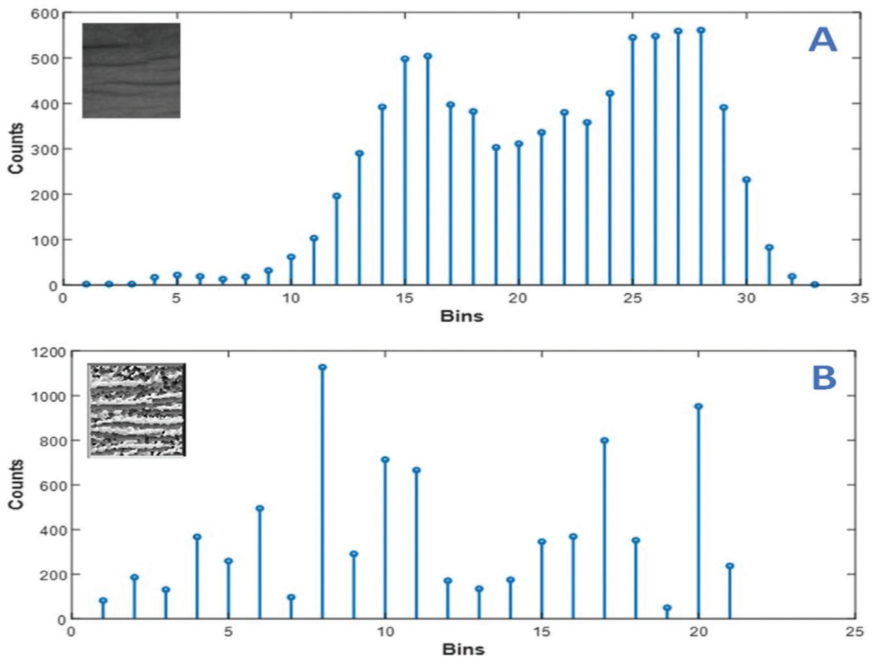

Fig. 9. Results of an FOK and LDN (with best-chosen parameters), A: Histogram counts for an FOK image before the LDN, B: Histogram counts for an FOK image after the LDN

4.4. COMPARISONS

Comparisons are considered with many feature extractions including state-of-the-art methods. Table 4 provides comparisons with various feature extraction methods for the identification based on the FOK.

These are the Surrounded Patterns Code (SPC) [1], Enhanced Local Line Binary Pattern (ELLBP) [2, 3], Local Binary Patterns (LBP) [4], Centralized Binary Patterns (CBP) [7], Center-Symmetric Local Binary Pattern (CSLBP) [8] and Local Binary Patterns for FOK (LBP-FOK) [5], respectively.

The table provides the Equal Error Rates (EER) for different feature extraction techniques for personal identification based on the finger's outer knuckle. The EER measures the accuracy of a biometric system, with a lower EER indicating better performance.

Table 4. Comparisons with various feature extraction methods for the identification based on the FOK

Reference	Feature extraction	Parameters	EER (%)
[27]	SPC	---	45.9
[28]	ELLBP	N=17, w1=0.7 and w2=0.3	29.53
[29]	LBP	P=8 and R=1	28.37
[30]	CBP	P=8 and R=3	23.33
[31]	CSLBP	P=8 and R=2	23.26
[32]	LBP-FOK	N=5	14.03
Proposed method	LDN	Mask of type Gaussian and Sigma=0.85	10.78

Among the traditional feature extraction methods, LBP and CLBP have lower EER than the other traditional methods (SPC and ELLBP). Specifically, LBP has an EER of 28.37%, which is slightly better than the EER of CBP (23.33%) and CSLBP (23.26%), but worse than the EER of LBP-FOK (14.03%) and LDN (10.78%).

LBP-FOK and LDN, which are more advanced feature extraction techniques, have significantly lower EER than traditional methods. LDN has the lowest EER (10.78%), followed by LBP-FOK (14.03%).

Overall, LDN performs best among the feature extraction techniques in the table, followed by LBP-FOK, CBP, CSLBP, LBP, ELLBP, and SPC in descending order of performance.

5. CONCLUSION

The LDN method offered a thorough and efficient methodology to evaluate FOK patterns for identification. LDN improves accuracy and robustness in identifying persons based on their FOKs by utilizing the input image, assessing edge responses in several directions and creating a robust encoding technique.

The result showed the proposed method's effectiveness and robustness with EER equal to 10.78%. It can be concluded that using the LDN pattern identification method is possible to identify people based on their FOKs in a trustworthy and accurate manner. This is because it creates a six-bit binary code that distinguishes between variations in texture intensity.

Various future studies can be suggested as exploiting the LDN for the patterns of fingerprint, finger inner knuckle and finger nail. In addition, more work can be carried out for using the LDN with FOKs in terms of verification.

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