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Effect of Blurred Fingerprints in Biometric Identification using Machine Learning

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Abstract

Biometrics has transformed identification using human traits, but challenges like privacy concerns and security vulnerabilities persist. Fingerprint biometrics, crucial for uniqueness, has evolved with digitalization and machine learning. The paper investigates blurring effects on fingerprint features, proposing machine learning for comparative minutiae-based matching. Gaussian blur impact on identification accuracy is studied, with a decline observed beyond a standard deviation (SD) of 0.3. FLANN matching score remains 100 % for SD in the range 0.1-0.3. The diminishing matching ratio and modified minutiae spatial pattern with increasing SD highlight the influence of blurring. The study assesses a machine learning system's tolerance to blurring, revealing poor matching beyond an SD of 0.4. Generally, the blurring is introduced because of skin scattering, optical blur, or motion blur, emphasizing the need for a pilot mechanism with standard reference fingerprints before scanning for developing future-ready fingerprint scanners.

Keywords: Biometric features; Fingerprint matching; Minutiae; Gaussian blurring; Minutiae matching score; Matching ratio; Gabor parameters.

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1. Introduction

Biometric technology has revolutionized personal identification and authentication by utilizing unique physiological and behavioral characteristics of individuals. Physiological traits such as fingerprints, facial structure, iris patterns, hand geometry, and DNA, along with behavioral traits like voice, gait, typing rhythm, and signature dynamics, provide high levels of distinctiveness, permanence, and resistance to forgery. These qualities make biometrics a reliable and increasingly adopted approach across domains such as security, healthcare, and forensics.

The core advantage of biometric systems lies in their ability to directly link an individual to their biological traits. However, the adoption of biometric systems at scale continues to face critical challenges, including privacy concerns over data storage, the threat of spoofing

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and cyber attacks, environmental sensitivity affecting accuracy, and the high cost of implementation in large-scale applications. Biometric identification relies on three essential processes: feature extraction, classification, and matching. Feature extraction algorithms isolate distinguishing patterns to generate identity templates. Classification algorithms categorize biometric data into known groups, while matching algorithms assess similarity between input and stored templates. Despite advancements, system performance may still degrade due to intrinsic factors such as aging, injuries, or illness, and extrinsic conditions like sensor noise, illumination variations, and background interference.

Among all biometric modalities, fingerprints are considered the most stable and accessible, offering high distinctiveness, permanence, and consistency over time. Their inherent uniqueness and reliability make them an ideal primary biometric trait for human identification. Fingerprints support advanced forensic investigations by enabling the determination of identity and providing clues about specific actions [1]. The fingerprint recognition systems typically analyze ridge flow, valley structures, and minutiae points specifically ridge endings and bifurcations which serve as unique identifiers [2], as illustrated in Fig. 1. Minutiae, defined by the distinct patterns formed by ridges and valleys, are the most critical features for identification. The precise location and orientation of ridge endings and splits along ridge paths enhance the accuracy of recognition.

Fingerprint features encompass various types of minutiae like crossover, core, bifurcation, ridge ending, island, delta and pore and additional fine-grained details used in automatic classification and minutiae extraction processes. On average, around 30 minutiae points are employed in fingerprint matching techniques [3]. The spatial distribution and arrangement of these points allow for effective discrimination between individual fingerprints.

Fig. 1. Important feature like minutiae and their characteristics in a given fingerprint[2].

Studies have shown that even genetically identical individuals, such as twins, do not share the same fingerprint patterns, further supporting their reliability. Traditional fingerprint classification involves detecting global patterns such as arches, loops, and whorls, along with specific minutiae like cores, deltas. With the advent of digital technology, fingerprint analysis has shifted from manual methods to automated systems using optical sensors and large databases for efficient identification [4].

Although minutiae points were once considered insufficient for fingerprint reconstruction, recent work suggests that partial reconstruction is possible. Nevertheless, a significant difference remains between the matching accuracy of original and reconstructed prints, reinforcing the need for robust and resilient recognition systems. In response to these challenges, machine learning (ML) techniques have been extensively adopted in fingerprint recognition tasks including feature extraction, classification, and matching. Techniques such as Support Vector Machines (SVMs), Genetic Algorithms (GAs), and Artificial Neural Networks (ANNs) have shown efficacy not only in fingerprint recognition but also in handling non-linear and noisy datasets [5,6]. These approaches are widely applied in areas ranging from stock market prediction [7], security [8]. More recently, Convolutional Neural Networks (CNNs) have enabled alignment-free recognition, improving system performance on distorted and partial fingerprint inputs.

Recent advancements in fingerprint identification highlight significant progress in visualizing and analyzing third-level features, such as pores, incipient ridges, ridge contours, scars, and creases. These microscopic features, often overlooked in earlier studies, are now recognized for their role in enhancing individualization, donor profiling, spoof detection, fingerprint age estimation, and even disease diagnosis [9]. As the demand for high-fidelity fingerprint recognition increases, the development of advanced fingerprint sensors including optical, capacitive, ultrasonic, and electromagnetic wave-based acquisition technologies has greatly improved the precision and reliability of fingerprint capture [10]. In forensic applications, the use of fluorescent organic materials for latent fingerprint imaging has further enhanced visualization on complex surfaces at crime scenes [11].

With the growing deployment of biometric identification systems, Automated Fingerprint Identification Systems (AFIS) have become integral to sectors such as law enforcement, border control, and consumer devices. Despite ethical concerns around data privacy, fingerprint recognition remains less intrusive than DNA or facial biometrics [3]. Fingerprints are generally classified into three types patent (visible), plastic (impression-based), and latent (invisible) each playing a crucial role in forensic investigations [12].

The combination of texture, minutiae, and frequency spectrum features in fingerprint analysis has been extensively explored using CNN-based frameworks. One approach addresses the limited usage of frequency spectrum in conventional systems and incorporates a minutiae attention module to improve feature extraction accuracy. Additionally, novel fingerprint-specific augmentation strategies have been proposed to boost model generalization [13].

Various fingerprint feature extraction techniques, including K-means clustering, Local Binary Patterns (LBP), Wavelet Packet Transform (WPT), and traditional minutiae-based methods, have been evaluated [14]. Among them, minutiae and K-means approaches stand out for their rotation invariance, computational efficiency, and uniqueness of extracted features. Moreover, researchers have reported that extracting valleys, rather than ridges, especially in blurred fingerprints, provides richer feature sets for subsequent matching stages. Filtering techniques such as median, Gaussian, Wiener, Kalman, and Gabor filters have proven effective in enhancing these valley structures [15]. In healthcare, fingerprints are employed to verify patient identities and detect fraudulent activities. A median filtering approach followed by hybrid binarization has demonstrated an average precision of 85.28%, particularly in neonatal units where accurate identification is crucial [16].

Deep neural networks (DNNs) are also employed in biometric systems, either for single or multimodal analysis, focusing on feature extraction, classifier design, and performance evaluation [17]. Classification of fingerprints based on minutiae patterns arch, loop, and whorl has been refined using CNNs [18]. Gan *et al.* [19] proposed a deep learning-based fingerprint classification using the SqueezeNet model, emphasizing reduced computational cost without compromising accuracy. Further, Michelsanti *et al.* [20] used two transfer learning-based CNNs VGG19-F (fast) and VGG19-S (slow) to classify fingerprint patterns using the NIST SD4 dataset. Both models were trained using data augmentation techniques such as flipping and rotation. The optimized networks achieved 94.4 % and 95.05 % accuracy, respectively, highlighting the potential of CNNs in fingerprint categorization.

In scenarios involving blurred or distorted fingerprints from crime scenes or low-quality sensors, automated systems struggle to achieve reliable matching. To tackle this, FDeblur-GAN was introduced, a conditional GAN-based model that includes auxiliary sub-networks: one for ridge extraction and another for ID verification. This multi-stage model, trained on a dedicated blurred fingerprint dataset, achieved 95.18 % matching accuracy [21].

For consumer-level devices, where computational resources are limited, lightweight deblurring networks are preferred. The SRN+ model, enhanced using pseudo-labeling and soft funnel labels, has demonstrated improved PSNR by +1 dB over MPRNet while reducing parameters by 70 %, thus making it suitable for embedded systems [22].

The issue of fingerprint alteration, such as deliberate distortion to evade recognition, is a growing challenge. The SOCOFing dataset provides 55,249 images with various alteration types like Z-cut, obliteration, and central rotation. A CNN trained on this dataset achieved 98.55 % accuracy, while a residual CNN pre-trained on ImageNet reached 99.88 % [23]. Moreover, encoding fingerprint ridge orientation and phase continuity using patch dictionaries has enhanced resistance to Type-I and Type-II spoofing attacks [24]

The impact of varying distortion levels on recognition accuracy was investigated [25]. The results indicated a linear degradation in performance; higher distortion led to increased false acceptance and rejection rates across 201 individuals' fingerprints. For, fingerprints affected by corruption or partial absence, generative CNNs have been used to reconstruct missing ridge patterns. These enhanced images were then passed through standard tools like MINDTCT and matched using MCC and BO-ZORTH3, yielding improved recognition on multiple public datasets [26].

Blurring caused by skin scattering, optical mismatch, and motion is a major source of degraded performance [27]. In particular, motion blur common during image acquisition significantly lowers accuracy in finger-vein and fingerprint systems. A modified DeblurGAN was proposed to restore motion-blurred images, effectively improving recognition under real-world conditions [28].

However, one critical aspect that remains underexplored is the effect of image blurring on fingerprint recognition accuracy. In real-world scenarios, blur often occurs due to motion, sensor limitations, or skin scattering, which can severely affect the quality of captured prints and the reliability of recognition. This study uniquely investigates the quantitative impact of Gaussian blurring on fingerprint identification accuracy using minutiae and Gabor features. A novel threshold of blurring tolerance is established, beyond which recognition performance significantly deteriorates. The use of the FLANN algorithm enables efficient matching under varied blur conditions. The findings offer valuable insights for developing robust fingerprint scanners equipped to handle real-world image degradation. The paper is structured as follows: Section 2 describes the proposed methodology, Section 3 discusses the experimental results, and Section 4 concludes with potential future directions.

2. Materials and Methods

Blurred fingerprints pose challenges in minutiae detection, affecting identification accuracy. Some fingerprint enhancement algorithms effectively reduce false minutiae but may still yield inaccuracies. Input image quality, influenced by factors like skin conditions and sensor noise, determines the success of pre-processing and minutiae extraction. Fingerprint recognition relies on reliable minutiae extraction, influenced by image quality and acquisition factors. The effect of blurring on biometric feature detection from the fingerprints is investigated using Sokotocoventry fingerprint dataset (SOCOFing) [30]. The dataset includes 6,000 fingerprint images collected from 600 subjects, featuring distinct attributes that enhance its usability for research and analysis. Each fingerprint image is accompanied by detailed labels indicating the subject's gender, as well as specific information about the hand and finger from which the print was taken. This comprehensive labelling provides valuable context for various studies, including those focused on biometric identification, gender-based analysis, and finger-specific pattern recognition. The overall methodology is shown in Fig. 2.

The system uses a compact, high-performance biometric device SLK20R USB Fingerprint Scanner by ZKTeco featuring a 500 ppi optical CMOS sensor that captures fingerprint images at 300×400 pixels with a 15×20 mm sensing area. It is designed to offer precise minutiae detail essential for accurate recognition. It operates reliably in a wide temperature range of -20 °C to 50 °C and 0–90 % humidity, making it suitable for varied environments. The data acquisition converts the raw scanned image into a standard digital format compatible with pre-processing algorithms. The reference image in each batch was modified by adding different amount of Gaussian blur with varying kernel size and the standard deviation using (1).

$$G_{2D}(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{\frac{x^2+y^2}{2\sigma^2}} \tag{1}$$

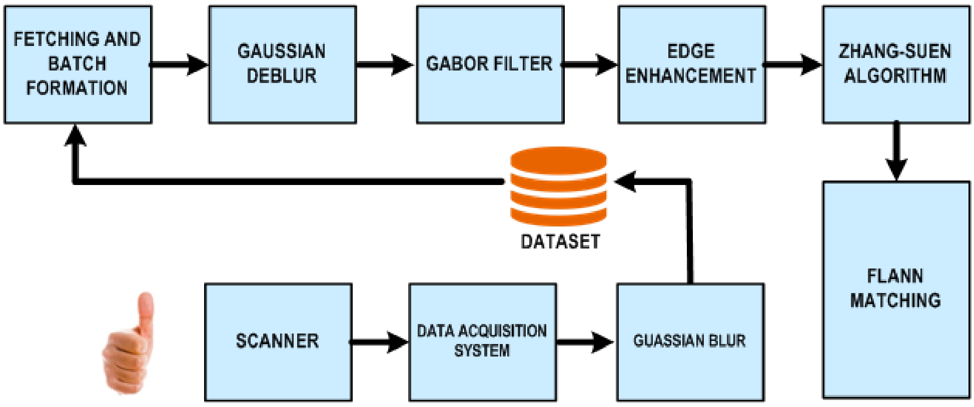


Fig. 2. Schematic of the methodology employed for proposed fingerprint matching.

where σ is the standard deviation (SD) of the distribution and (x,y) represents the spatial coordinates. The standard deviation determines the extent of the blurring affecting the high frequency content of the image resulting in modification of the minutiae points within the given fingerprint image. Images from the dataset are fetched and grouped into batches for efficient processing. Each batch includes a reference (original) image and one or more blurred versions. The batch-wise processing helps assess how blurring impacts minutiae extraction and matching accuracy. For extracting unique patterns that are used for the identification, the fingerprint image is processed for Gabor parameters and ridge contour estimation. The input mage is converted to grey scale. Noise reduction and contrast enhancement are carried out during the pre-processing step. Gabor filters are highly effective for capturing both local orientation and frequency details from fingerprint images. These filters are mathematically tuned to enhance fingerprint structures and suppress irrelevant noise. By adjusting a Gabor filter to specific frequencies and orientations, it is possible to extract precise local frequency and orientation information from the image. This tuning process enables the filter to optimize the detection of relevant features within the fingerprint. Sobel operator is used to calculate the gradient and based on the gradient information the orientations of ridges are determined. The extracted ridges are enhanced by suppressing non-maximum values in the direction perpendicular to the ridge orientations. This is followed by non-maximum suppression, which sharpens ridge continuity and supports clearer boundary formation. Adaptive thresholding is used to handle variations in image intensity and converting the ridges map to binary. The small and isolated regions are then removed to smoothen the ridge segment thereby creating continuous ridge structures. Skeletonized representation of the binary ridge image is achieved by Zhang-Suen algorithm. This ensures that extracted minutiae (ridge endings and bifurcations) are geometrically accurate.

The parameters are matched using FLANN (Fast Library for Approximate Nearest Neighbors) algorithm. It is a library of algorithms that is usually optimized for fast nearest neighbor search in the large datasets and high-dimensional features. FLANN is used to find matches between two fingerprint images by generating good key points using a ratio test based on the distance between the descriptors. The total number of key points generated will be greater than the two key points obtained from two images. Based on the number of key points obtained, key points are generated in both images, and accuracy is obtained [31]. Fingerprint matching involves calculating the Euclidean distance between feature vectors derived from the fingerprints being compared. This distance measures how similar the feature vectors are to one another. The smaller the Euclidean distance, the closer the match between the two fingerprints. The minimum score obtained from this distance calculation indicates the best alignment between the fingerprints, suggesting a higher likelihood that the fingerprints belong to the same individual. This process ensures accurate and reliable identification by quantifying the degree of similarity between the fingerprint features. If the Euclidean distance between two feature vectors is less than a threshold, then the decision that "the two images come from the same finger" is made, otherwise a decision that "the two images come from different fingers" is assumed. The results obtained from minutiae and Gabor parameters matching are statistically analysed.

3. Results

The results of the investigation into the impact of Gaussian blurring on fingerprint identification accuracy are presented in Table 1 and Fig. 3. These results offer insight into how varying levels of image blur influence the system's ability to accurately extract and match fingerprint features. Specifically, the study examines the relationship between the standard deviation (SD) of the Gaussian blur and two primary evaluation metrics: the matching ratio and the FLANN matching score. The matching ratio is defined as the ratio of the number of matched minutiae points to the total number of minutiae points extracted from the reference fingerprint. For this study, the reference fingerprint contained a total of 754 minutiae points. In contrast, the FLANN matching score represents the accuracy of feature matching based on Gabor filter parameters, which are particularly effective in capturing both orientation and frequency components of fingerprint ridges.

Table 1. Variation of minutiae matching ratio and FLANN matching score with standard deviation (SD) of the Gaussian blur added to the target fingerprint image.

S. NO.	SD	Matched	Ratio	Score
1	0.1	754	1.0	100
2	0.2	754	1.0	100
3	0.3	740	0.98	100
4	0.4	646	0.85	78
5	0.5	484	0.64	42
6	0.6	358	0.47	35
7	0.7	239	0.316	21
8	0.8	159	0.21	23
9	0.9	121	0.16	23
10	1.0	102	0.13	21

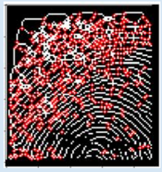
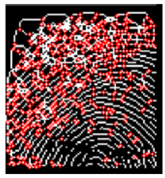
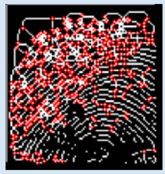
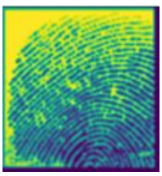
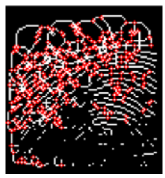
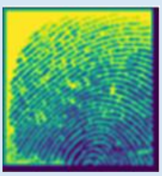
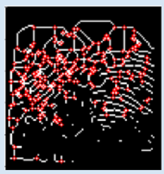
SD	Blurred fingerprint	Pre-processed fingerprint	Minutiae pattern
0.1			
0.3			
0.5			
0.7			
0.9			

Fig. 3. The extraction of minutiae is affected by the amount of Gaussian blur present in the reference fingerprint. The first column shows the SD used for introducing the blur in the fingerprint and the resulted image is shown in column 2. The image obtained after thresholding and contouring is shown in column 3. The extracted minutiae are marked as red and shown in column 4.

In this case, 128 Gabor parameters were extracted from the reference fingerprint, and the FLANN matching score is expressed as the percentage of these parameters that were successfully matched between the reference and the blurred images. To evaluate the impact of blur, Gaussian noise was added to the reference fingerprint images by varying the SD from 0.1 to 1.0, while the kernel size was adjusted from 3×3 to 21×21. Preliminary tests revealed that kernel sizes greater than 3×3 introduced significant distortion, rendering the matching process unreliable. Hence, for consistency and reliability, the final experiments were carried out using a 3×3 kernel size.

Analysis of the results reveals three distinct performance regions with respect to the SD values. For SD values in the range of 0.1 to 0.3, both the matching ratio and FLANN score remained close to 100 %, indicating a region of best matching. This suggests that the system is highly tolerant to minor blurring and can still accurately identify the fingerprints. At SD = 0.4, the system exhibited a drop in both metrics, identifying a region of acceptable matching, where recognition is still possible but slightly degraded. Beyond this point, particularly from SD = 0.5 to 1.0, a significant decline in matching performance is observed. This marks the region of poor matching, where the identification reliability falls below acceptable thresholds. Fig. 3 further illustrates these observations by visually depicting the progressive distortion of minutiae patterns as SD increases. It also includes images of the blurred fingerprints post-Gaussian filtering and their corresponding pre-processed versions following thresholding and ridge contour enhancement. These visual cues confirm the numerical findings, showing how increased blurring not only reduces the number of matched minutiae but also alters their spatial configuration, thereby degrading the ability of the system to perform accurate identification.

4. Conclusion

This study investigated how varying degrees of Gaussian blur affect the accuracy of fingerprint recognition using a machine learning-based approach that combines minutiae and Gabor features. Through experimentation with different standard deviation (SD) values, it was found that the system maintains high recognition accuracy for SD values up to 0.3, where both the minutiae matching ratio and FLANN score remained near 100 %. However, a noticeable decline in performance began at SD = 0.4, and further degradation was observed as the blur increased. The study effectively identified three performance regions optimal, acceptable, and poor based on SD values, helping to quantify the tolerance limit of fingerprint recognition systems under blur conditions. The results emphasize that blurring caused by motion, skin scattering, or optical imperfections significantly alters the spatial configuration of minutiae points and reduces the system's ability to correctly match fingerprint images. These findings are critical for designing robust and accurate fingerprint scanners capable of functioning in real-world environments where image degradation is common. For future enhancement, the study suggests incorporating a pilot mechanism using standard reference fingerprints to assess image quality before final capture. This proactive step could help ensure that input images meet minimum quality thresholds, improving system reliability in practical deployments.

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