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Development of an Adaptive Fingerprint Multi-Filter Enhancement Technique for Improved Reliability in Biometric Systems

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Abstract
Fingerprint identification system is among the most dependable biometric identifiers due to its uniqueness and accessibility, but distorted fingerprint images usually reduce recognition accuracy. Existing multi-filter enhancement techniques improve ridge quality through a fixed sequence approach which usually leads to over-enhancement and computational complexity. This study proposed an optimized multi-filter technique based on Fingerprint Noise Detection and Adaptive Removal (FINDAR) approach which detects noise patterns and applies adaptive de-noising techniques with reduced runtime and memory usage. FINDAR was implemented in MATLAB using 6000 real fingerprint images from Sokoto Coventry Fingerprint (SOCOFing) repository. Contrast enhancement and segmentation technique were employed as pre-processing steps to increase the visibility of the fingerprint images and to separate the foreground from the background, respectively. The developed model was evaluated solely using multi-noise detection accuracy and against Coherence Diffusion+Log-Gabor filter, Finger U-Net, Radial Hilbert Transform Edge Enhancement (RHLT) and Gabor+HE+CLAHE Multistage Enhancement Technique using Structural Similarity Index (SSIM), Natural Image Quality Evaluator (NIQE), Entropy, Execution time and Memory Usage, as metrics. FINDAR achieved high multi-noise detection accuracy average of 91.7% and also outperformed the benchmarked models with the highest SSIM (0.93), lowest NIQE (3.11) and highest entropy (7.02). FINDAR also demonstrated competitive runtime efficiency (17.71ms) and moderate CPU usage (295MB) compared to others. It was also observed that Finger U-Net that used deep learning approach recorded fastest runtime (13.9ms) but consumed significantly higher memory (970MB). These outcomes showed how effectively FINDAR addressed the issue of poor-quality fingerprint photos with minimal processing resources for practical biometric applications.

***Keywords*:** Multi-filter technique, Fingerprint enhancement, Adaptive removal

1.0 Introduction

The rise in the adoption of fingerprint recognition system in various areas including mobile authentication, banking, access control, attendance management and forensic investigation has amplified the need for efficient and accurate fingerprint enhancement and recognition techniques (Shams *et al.,* 2023). Despite the advantages of fingerprint as a biometric identifier, its overall recognition performance is highly relying on the quality of the fingerprint images acquired during enrolment and verification stages. They are often affected by different forms of noise and distortion usually caused by skin conditions, moisture, scanner imperfections and improper finger placement during acquisition (Riaz *et al.*, 2024) as demonstrated in Figure 1. These quality degradations obscure ridge structures, hinder accurate minutiae extraction and consequently increases the False Acceptance Rate (FAR) and False Rejection Rate (FRR) thereby reducing the reliability and security of fingerprint biometric system (Fierez *et al.*, 2022).

Figure 1: Noisy Fingerprint Image Samples

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To mitigate these issues, several fingerprint enhancement methods have been proposed which includes single-step approach like segmentation, filtering, histogram equalisation and multi-filter enhancement techniques both aimed at improving the ridge clarity and reduce fingerprint noise prior to feature extraction (Bhargava *et al.*, 2024). However, single-step approaches are computationally efficient but often ineffective against severe or overlapped noise conditions, while multi-filter methods usually lead to excessive smoothing, blur fine ridge details and increase computational overhead (Kumar *et al.*, 2023). They are also both static in nature and lack adaptability to the varying noise characteristics present in fingerprint images. Such limitations negatively affect minutiae extraction accuracy and reduce the overall efficiency of fingerprint recognition systems (Socheat, 2020).

Due to the heterogenous nature of fingerprint noise, there is a pressing need for an intelligent and adaptive enhancement approach capable of dynamically identifying the noise characteristics of a fingerprint image and applying the most appropriate de-noising technique accordingly. Oguntunde and Momoh (2023) also demonstrated that utilizing the complimentary advantages of several algorithms in an intelligent model can greatly enhance detection and decision-making performance over single-model approaches. Motivated by this concept, this study proposed a Fingerprint Noise Detection and Adaptive Removal (FINDAR) technique to improve fingerprint image quality through adaptive multi-filter enhancement technique by reducing FAR, FRR and Equal Error Rate (EER) thereby increasing the fingerprint recognition accuracy with minimal computational overhead.

2.0 Related Works

Most of the fingerprint enhancement algorithms proposed in the literature have no difficulty in enhancing nearly good quality fingerprint images but the task becomes challenging when it comes to very poor quality fingerprint images.

Conventional fingerprint image enhancement approaches mainly relied on filtering techniques. Sherlock *et al*. (1994) proposed a band-pass filtering method that extracts ridge features and suppressed background noise to improve the visibility of fingerprint ridge patterns but the method demonstrated poor performance under heavy noise conditions. Greenberg *et al.* (2002) introduced a modified Gabor filter which combined anisotropic filtering and oriented low-pass filtering to enhance ridge continuity and improve local ridge structure preservation better when compared to earlier filtering methods. It was also detected that the approach still struggled with highly noisy fingerprint regions, indicating a persistent limitation of traditional filtering techniques.

Studies shifted towards model-based fingerprint enhancement techniques aimed at improving ridge structure representation. Gottschlich (2012) developed polynomial and zero-pole models that provided a mathematical representation of fingerprint ridges using fixed ridge frequency, contributing to more structured ridge reconstruction and enhancement. However, the identification accuracy remained relatively low. Another Author, Zhao *et al.* (2014) proposed a ridge structure dictionary-based method that improved ridge reconstruction quality and enhanced identification rates through the use of learned ridge patterns, the method also suffered from high computational cost and poorly defined confidence measures.

To address these limitations in *Zhao et al.* (2014), sparse representation and dictionary learning methods were introduced by Yang *et al.* (2014). This study proposed a multi-scale patch-based sparse representation technique which effectively enhanced local ridge details by exploiting sparse image representations across multiple scales, the method also ignored global ridge structures, leading to poor performance on low-quality fingerprint images. Likewise, Ram and Rodriguez (2018) employed a spectral dictionary approach that improved frequency-domain ridge enhancement and noise suppression. However, the method allowed noise leakage into reconstructed images, which reduces its effectiveness in enhancing degraded fingerprint images. Moreover, Yousef and Hossain (2018) also combined Edge Directional Total Variation (EDTV), image quality enhancement, and minutiae reconstruction techniques, resulting in improved ridge clarity and minutiae preservation but the method failed to effectively handle mixed noise conditions and severely degraded fingerprint images.

Advanced feature-based and learning-driven approaches were later explored by Engelsma *et* *al.* (2019). The method applied the Scale-Invariant Feature Transform (SIFT) technique for fingerprint features enhancement that improved the robustness of feature extraction under varying image conditions but the method struggled with partial and poor-quality fingerprint impressions. Kim *et al.* (2019) employed Generative Adversarial Networks (GANs) which learn fingerprint ridge distributions and generate enhanced fingerprint images to achieve moderate improvements in ridge restoration quality, the study still face challenges in generating spurious features when sufficient ridge information was unavailable.

Pu *et al.* (2020) proposed a two-stage spectrum boosting technique that enhanced ridge frequency information and improved ridge contrast in fingerprint images, its effectiveness was also highly dependent on the availability of strong ridge signals. Moreover, Qin and El-Yacoubi (2020) utilized minutiae density and orientation fields to improve fingerprint ridge reconstruction and feature consistency. Despite these improvements, the method relied heavily on local patterns and performed poorly on low quality fingerprint images.

Wei *et al.* (2021) developed a GAN-based denoising architecture which effectively reduced image noise and enhanced ridge visibility through deep learning-based feature extraction, it is limitation lies on the method's requirement for large training datasets and complex training procedures, limiting its practical applicability. Recently, Shams *et al.* (2023) introduced a multi-filter enhancement framework that combined diffusion coherence filtering and log-Gabor filtering to improve ridge continuity, noise reduction, and overall fingerprint image quality but computational complexity was also increased, making it unsuitable for real-time applications.

Gavas and Namboodiri (2023) also developed Finger U-Net architecture which is a deep learning-based multi-filter enhancement framework integrating wavelet transforms and attention mechanisms. The approach improved feature extraction capability, ridge enhancement accuracy, and noise suppression performance across different fingerprint quality levels, limited training datasets is the drawback that reduces its generalization ability across various acquisition devices, while computational cost remained high. Another study by Wu *et al.* (2024), introduced a radial Hilbert transform-based enhancement technique which improved edge detection and ridge boundary representation in fingerprint images but failed to adapt to varying ridge orientations and complex fingerprint patterns.

Most recently, Evans *et al.* (2025) proposed a classical enhancement pipeline combining Adaptive Histogram Equalization (AHE), Contrast Limited Adaptive Histogram Equalization (CLAHE), and Gabor filtering. The approach improved image contrast, ridge visibility, and local feature enhancement. However, the method remained highly dependent on accurate orientation estimation which limits performance under severe noise and distortion conditions.

3.0 Methodology

3.1 Adaptive Fingerprint Enhancement Model

This study proposed an adaptive fingerprint enhancement model termed Fingerprint Noise Detection and Adaptive Removal (FINDAR), for improving the quality of degraded fingerprint images prior to feature extraction. The model integrates contrast enhancement and segmentation technique to improve fingerprint image visibility and to separate the foreground from the background respectively, as shown in Figure 2. From the model in Figure 2, given an input grayscale fingerprint image $I\,(x,y)$, contrast enhancement was firstly employed using histogram equalisation which improves the visibility of the ridge structures. The enhanced image is written as:

$$I_e(x,y) = T(I(x,y) \qquad \ldots 1$$

Where $T(.)$ represents the histogram equalization function

The enhanced image was then segmented to isolate the region of interest (ROI) known as foreground from the background using a binary mask $M(x,y)$, to remove the background pixels and preserves the useful foreground for subsequent fingerprint image analysis:

$$I_{ROI}(x,y) = I_e(x,y)\, \times\, M(x,y) \qquad \ldots 2$$

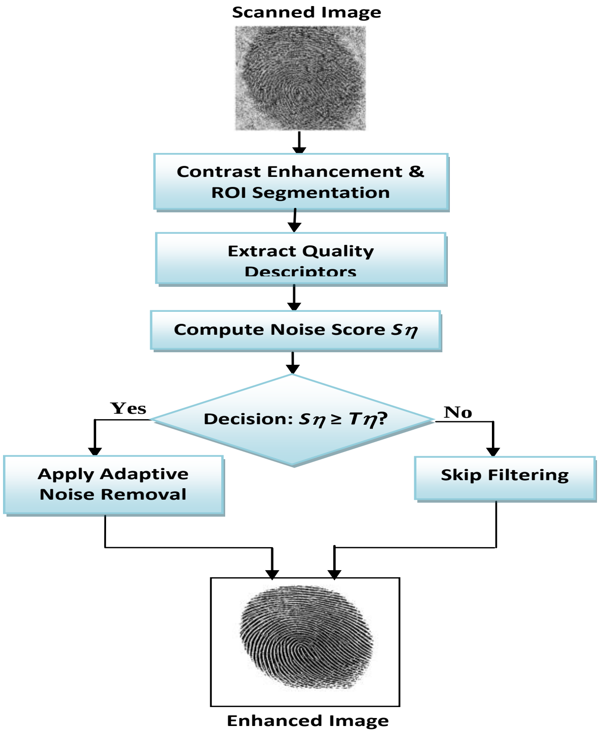

Figure 2: Adaptive Fingerprint Noise Detection and Removal Model

To determine the noise characteristics present in the segmented image, statistical descriptors such as Variance of Laplacian, Standard deviation, Histogram distribution measure, Frequency-domain measure, Local Contrast measure and Blockiness measure were combined into a noise descriptor vector:

$$N = [V_L, \sigma, H_T, F_q, C_L, B_k] \quad ...3$$

Where V_L is the Variance of Laplacian, σ is the Standard deviation, H_T is the Histogram distribution, F_q , is the Frequency domain, C_L is the Local Contrast and B_k is the Blockiness measure of a degraded fingerprint image.
A decision function was applied to identify the noise class thus:

$$C_n = f(N) \quad ...4$$

Where $C_n \in \{c_i, c_2, c_3, c_4, c_5, c_6\}$ denotes salt-and-pepper, Guassian, motion blur, speckle, smudging or compression artifact noise.

A composite noise index that aggregates all noise determinants was introduced and then compared against a certain threshold:
Unified noise score =

$$N_k(x) = \sum_{i=1}^{m} w_i f_i(x) \quad ...5$$

Where $f_i(x)$ represents noise determinants, w_i are weighting coefficients reflecting their importance, $N_k(x)$is the overall noise index for the image x.

The decision rule for noise presence:

$$N_k(x) \geq T_k \quad ...6$$

Where T_k is the predefined threshold for noise type k, if the condition is satisfied, k is declared present, otherwise, it is considered absent or insignificant.

Based on the detected noise(s) an adaptive filtering function selects the most suitable de-noising operation(s) thus:

$$I_f = \emptyset(C_n, I_{ROI}) \quad ...7$$

Where $\emptyset$ applies median filtering for salt-and-pepper noise, Guassian filtering for Gaussian noise, Wavelet transformation for Motion noise, Wiener filtering for Speckle noise, Gabor filter for Smudging noise and Spectral subtraction for Compression artifact noise. The adaptive technique ensures that de-noising is based on the observed image degradation rather than a fixed enhancement sequence.

3.2 Dataset and model performance evaluation metrics

The developed FINDAR framework was implemented with MATLAB R2024a image processing toolbox using the Sokoto Coventry Fingerprint (SOCOFing) dataset which contains 6000 fingerprint images captured under varying acquisition conditions and exhibiting practical degradation characteristics commonly encountered in biometrics. Performance evaluation of the developed model was done using multi-noise detection accuracy to correctly identify all the degradation characteristics simultaneously present within a fingerprint image and in comparison with existing models using Structural Similarity Index (SSIM), Natural Image Quality Evaluator (NIQE), Entropy and Execution time/memory usage for structural preservation, noise reduction quality, information retention and computational efficiency, respectively.

i. Accuracy = $\frac{1}{N}\sum_{i=1}^{N}\frac{|Y_i \cap \hat{Y}_i|}{|Y_i \cup \hat{Y}_i|}$ …8

Where:

- N represents the total number of fingerprint samples,
- Y_i is the actual set of degradation types presents in fingerprint image i,
- $\hat{Y}_i$ represents the set of degraded types predicted by FINDAR,
- $Y_i \cap \hat{Y}_i$ represents correctly detected degradation types and
- $Y_i \cup \hat{Y}_i$ represents the union of actual and predicted degradation labels

This measures the degree of overlap between actual degradation types and the degradation types predicted by the developed framework.

ii. $SSIM(x,y) = \frac{(2\mu_x\mu_y + C_i)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_i(\sigma_x^2 + \sigma_y^2 + C_2)}$ ..9

Where:

- μ_x and μ_y represent image mean intensities
- σ_x^2 and σ_y^2 represents variances
- μ_{xy} represents covariance
- C_1 and C_2 are stabilization constants

This measures the preservation of ridge orientation, local texture consistency and structural relationships. An SSIM value closer to 1 indicates that fingerprint ridge structures remain highly preserved after enhancement.

iii. $NIQE =$
$\sqrt{(v_i - v_2)^T(\frac{\Sigma_1 + \Sigma_2}{2})^{-1}(v_1 - v_2)}$ …10

Where: nv_1 is the mean feature vector of the enhanced fingerprint images, nv_2 is the mean feature vector of the referenced quality images, $sigmal_1$ is the covariance matrix of the enhanced image features, $sigmal_1$ is the covariance of matrix of the reference image features while T is the Transpose operation

Lower NIQE after enhancement implies that the enhanced fingerprint image becomes more visually natural and less distorted.

iv. $Entropy = -\sum p(i)log_2 p(i)$ …11
Where $p(i)$ represents the probability distribution of image intensity levels, a moderate increase in entropy value suggests that ridge details and useful biometric information are better preserved and represented.

v. Execution Time: If one image takes processing time t_i seconds and N images are tested, the execution time taken is represented as:

$$\acute{t} = \frac{1}{N}\sum_{i=1}^{N} t_i \quad ...12$$

vi. Memory usage: If m_i is the memory usage during the processing of image i, peak memory is calculated thus:
$m_{peak} = \max(m_i)$ ... 13

4.0 Results and Discussion

4.1 Effect of preprocessing on live-scan fingerprint images

The contribution of contrast enhancement and segmentation of the dataset was evaluated using balanced accuracy as shown in Table 1. To achieve this, pixel-level confusion matrix was employed whereby each fingerprint is defined per pixel as:

Positive pixel=Ridge, Negative pixel=Valley

Then:

True Positive (TP) = Predicted ridge and true ridge

True Negative (TN) = Predicted valley and true valley

False Positive (FP) = Predicted ridge but actually valley

False Negative (FN) = Predicted valley but actually ridge

Where TPR = True Positive Rate, TNR = True Negative Rate

$$Balanced\ Accuracy = \frac{TPR + TNR}{2}$$

$$Where\ TNR = Specificity = \frac{TN}{TN + FP} = 1 - FPR$$

$$TPR = Recall = Sensitivity = \frac{TP}{TP + FN}$$

Input Image Type	Balanced Accuracy (%)
Raw Fingerprint Image	51.40
Contrasted & Segmented Image	95.35

From the table 1, it can be deduced that the preprocessing steps has improved balanced accuracy by 43.95% from 51.40% to 95.35% thereby improving the effectiveness of FINDAR

4.2 Fingerprint Noise Detection Accuracy

Table 2 illustrates the different categories of noise detected and their accuracies across the fingerprint dataset, including salt-and-pepper, Gaussian, motion blur, smudging, speckle and compression artifact noise. Each fingerprint image may contain one or multiple noise types, which shows the complexity and overlapping nature of noise in real-world fingerprint images. This structured output provides a foundation for the subsequent adaptive noise removal stage, where appropriate enhancement techniques were selectively applied according to the identified noise type(s).

Table 2: Multi-Noise Detection Accuracy of FINDAR

S/N	Noise Type	Detection Accuracy (%)
1.	Salt & Pepper noise	97.2
2.	Gaussian noise	94.5
3.	Motion blur noise	91.7
4.	Speckle noise	91.3
5.	Smudging noise	88.4
6.	Compression artifacts	86.9
	Average detection accuracy	91.7

The experimental results from Table 2 show that the developed FINDAR achieved the highest detection performance for Salt & pepper and Gaussian noise due to their distinguishable statistical characteristics within the fingerprint image. Slightly slower detection accuracy was observed for smudging and compression artifact degradation because such distortions may exhibit structural similarities with other local fingerprint degradations.

The overall detection accuracy confirms the robustness of the developed adaptive noise removal technique in identifying multiple simultaneous degradation conditions affecting fingerprint images.

4.3 SSIM, NIQE, and Entropy of the developed model Vs existing models

The structural preservation, image quality and information retention capacity of the raw fingerprint image and the enhanced fingerprint image from FINDAR against Coherence Diffusion+Log-Gabor filter, Finger U-Net, Radial Hilbert Transform Edge Enhancement (RHLT) and Gabor+HE+CLAHE Multistage Enhancement Technique was evaluated and recorded in Tables 3 and 4 respectively:

Table 3: SSIM, NIQE and Entropy of the original fingerprint image

Dataset	**SSIM**	**NIQE**	**Entropy**
Original image	0.69	5.83	6.26

The raw degraded fingerprint image produced low SSIM, high NIQE and low entropy that indicate poor structural similarity, low perceptual quality and poor information retentions respectively due to the presence of multiple degradation conditions affecting the ridge continuity and local structural consistency as shown in Table 3.

Table 4: Comparison of SSIM, NIQE and Entropy of the Enhanced fingerprint images

S/n	Method	SSIM	NIQE	Entropy
1.	Coherence diffusion + Log-Gabor filter	0.80	4.81	6.60
2.	Finger U-Net	0.87	3.99	6.87
3.	RHLT	0.77	5.18	6.43
4.	CLAHE+HE+AHE	0.74	5.62	6.31
5.	Developed FINDAR	0.93	3.11	7.02

After enhancement, all methods improved ridge-valley clarity to varying degrees. However, the proposed FINDAR model achieved the highest SSIM, lowest NIQE and highest entropy values, indicating superior preservation of fingerprint ridge structures, superior perceptual and improved preservation of useful fingerprint information after enhancement, respectively as shown in Table 4.

This demonstrated that the developed adaptive multi-filter technique effectively suppresses degradation while minimizing structural degradation, improving overall visual quality and preservation of useful fingerprint information after enhancement.

4.4 Comparison of Computational Efficiency

Peak Run-time and memory usage of the developed model was also evaluated under the same working conditions and dataset against Coherence Diffusion+Log-Gabor filter, Finger U-Net, Radial Hilbert Transform Edge Enhancement (RHLT) and Gabor+HE+CLAHE Multistage Enhancement Technique as illustrated in Table 5:

Table 5: Run-time and Memory Usage Evaluation

Method	Run-time (ms/image)	Memory Usage (MB)
Diffusion +Log-Garbor Filter	31.80	410
Finger U-Net	13.90	970
RHLT	22.60	330
Gabor+HE+CLAHE	36.40	455
Developed FINDAR	17.71	295

From Table 5, it was observed that Finger U-Net approach that used deep learning technique recorded the least peak run-time of 13.90ms but significantly high memory usage of 970MB. The FINDAR model approach provided the best trade-off between runtime and memory usage of 17.71ms and 295MB respectively, indicating low enhancement time with lower computational overhead compared to other approaches.

5.0 Conclusion and Future Work

Unlike conventional static fingerprint enhancement methods that apply a fixed filtering operation sequence regardless of degradation type, FINDAR performs adaptive noise-aware enhancement based on degradation characteristics detected within the fingerprint image. The adaptive capability contributes significantly to the robustness and effectiveness of the developed model under varying fingerprint degradation conditions.

The experimental results show that the developed FINDAR model outperformed the selected benchmark methods in most of all evaluation metrics. Finally, the model can detect multiple distortions but performance reduces when multiple degradations overlap strongly in the same region. Therefore, handling severe mixed noise condition more explicitly is an important direction for future improvement.

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