Learning Ridge Structures: Adaptive CNN-Based Local Orientation and Frequency Estimation for Fingerprints

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***Abstract*—Fingerprint identification is one of the most well-understood and widely used biometric methods for identifying individuals, relying on the accurate identification of ridge structures in fingerprint images. There has been significant work to date on estimating ridge information (i.e., orientation) in fingerprint images. However, estimating ridge quantity (i.e., ridge frequency) presents challenges, especially for noisy or low-quality images. In this work, we propose an end-to-end solution using Convolutional Neural Networks (CNNs) to simultaneously estimate both ridge frequency and ridge orientation from fingerprint images. The proposed method includes preliminary processing to extract the fingerprint area from an image and orientation encoding to facilitate the network's learning process. The system has been trained with enhanced data and dense pixel-wise supervision to enhance noise and low contrast robustness. The system was evaluated on a typical fingerprint dataset and it yielded a mean absolute percentage error (MAPE) of 4.58 for frequency estimation leading to a substantial improvement over traditional image processing methodology. Additionally, this method is easily adaptable to real-time implementations. In this work, we illustrate how combining domain knowledge with modern machine learning approaches can lead to better accuracy and overall reliability in fingerprint analysis.**

***Index Terms*—Fingerprint Analysis, Local Orientation Estimation, Frequency Estimation, Adaptive CNN, Ridge Structure Learning, Biometric Feature Extraction.**

I. Introduction

Fingerprint recognition is among the most consistent and commonly used biometric techniques for personal identification because of its singularity and simplicity [1]. Two major features, which are at the core of fingerprint analysis, are **ridge orientation** and **ridge frequency** [2]. These two features capture the local structure and flow of ridge patterns and are vital in undertaking image enhancement, minutiae extraction, and proper matching [3].

Existing techniques for estimating ridge orientation and frequency are based on hand-designed filters or gradient-based methods [4]. While useful for clean high-quality images, they are not robust when applied to noisy, low-quality, or incomplete fingerprint images [5]. This weakness reveals a critical research gap: current Convolutional Neural Network (CNN) models are typically optimized for clean data and lack generalization to distorted or degraded fingerprint inputs [6].

The proposed adaptive CNN-based approach overcomes these challenges by estimating ridge orientation and frequency simultaneously from raw fingerprint images. The proposed model utilizes domain-specific preprocessing methods such as XSFFE (Extended Synthetic Fingerprint Feature Extraction) and SNFFE (Synthetic Normalized Fingerprint Feature Extraction), which improve learning through generation of clean synthetic ridge patterns and normalized fingerprint data [7]. The system is trained under data augmentation and dense pixel-wise supervision to enhance robustness to noise, smudging, and poor contrast [8].

Significant contributions of the work are:

- Design of an adaptive CNN architecture coupled with XSFFE and SNFFE preprocessing for effective feature learning [18].
- Strong estimation of ridge orientation and frequency even under noisy, low-quality, or distorted fingerprints [19].
- Pixel-wise dense supervision, allowing the model to learn fine-grained local ridge pattern variations.
- Benchmark test shows that MAPE (mean absolute percentage error) in the frequency estimation is only 4.58 and better real-time performance compared with conventional method [10].

This paper presents an example of how developing a fusion-based deep learning approach, animated correctly around the domain of fingerprints, accelerates in both precision and robustness of fingerprint processing, advancing published fingerprint biometrics research [20].

II. Related Works

Fingerprint classification has long been seen as the gold standard for biometric recognition systems. Research in this area can be divided into three main approaches:

A. Gradient and Fourier-Based Approaches

Early methods focused on handcrafted techniques such as gradient-based and Fourier-based methods for estimating ridge orientation and frequency. Ji et al. [1] suggested ridge projection techniques for orientation estimation, while Gottschlich et al. [2] improved fingerprint images using curved Gabor filters. Although these traditional methods are effective on clean, high-quality images, they often struggle with noisy, low-quality, or partial fingerprint data [3].

B. Filter-Bank Methods

To improve frequency estimation, filter-bank approaches like Gabor filters and Butterworth filters were used [4]. Xu et al. [5] introduced sparse orientation field modeling using FOMFE (Fourier Orientation Model for Fingerprint Estimation), which allows for a compact and efficient representation of ridge structures. These approaches improved performance on a broader range of fingerprints but still faced challenges in dealing with severe distortions and noise.

C. CNN-Based and Adaptive Methods

With the rise of deep learning, Convolutional Neural Networks (CNNs) have been used for fingerprint recognition. Takahashi et al. [6] proposed a multi-task CNN model for joint extraction of texture, minutiae, and frequency features, allowing for integrated analysis. Chinnappan et al. [7] furthered this work by creating end-to-end models for fingerprint classification and feature extraction, showing significant accuracy gains over traditional methods.

Cappelli et al. [8] presented a dual-branch adaptive CNN architecture that estimates orientation and frequency while using patch-wise attention mechanisms. Their research also addressed an important gap by introducing the FFE dataset, which provides much-needed ground truth for frequency estimation.

Alibeigi et al. [9] concentrated on real-time ridge orientation estimation, emphasizing efficiency in practical use cases. Hong et al. [10] reviewed fingerprint database indexing methods that are valuable for large-scale recognition systems. Cappelli et al. [11] examined challenges in fingerprint recognition systems, including data distortion, low image quality, missing ridge structures, and poor legibility.

D. Research Gaps and Motivation

Despite the progress in CNN-based fingerprint analysis, significant gaps remain:

- There is a lack of large, publicly available frequency ground-truth datasets for model training and evaluation [12].
- Existing models show limited robustness when applied to noisy, low-quality, or distorted fingerprints [13].
- Many methods still depend on patch-wise or block-wise analysis, which struggles to capture global ridge structure effectively [14].

This highlights the need for a robust, adaptive end-to-end CNN architecture that can directly estimate ridge orientation and frequency from raw fingerprint images [15]. It should include preprocessing modules (XSFFE, SNFFE) and pixel-wise dense supervision to address real-world challenges [16].

Fingerprint analysis has been crucial to biometric recognition systems for decades. A significant amount of research has focused on improving local ridge orientation and frequency estimation because these features are essential for image enhancement, minutiae detection, and matching [17].

to look at. It could be done by adding more parts that help the network focus on important parts of the picture.

III. Proposed Methodology

A. Dataset

The FFE dataset is meant to be used for research and evaluation of features such as ridge orientation, ridge frequency, and foreground region detection on the fingerprint image. It is a classified set of fingerprint images which can advice the comparison and building of models for techniques that use to enhance ridge in purposive, because it divides also a quality based class (Bad or Good).

Validating adaptive CNN architectures for orientation and frequency field mapping. Understanding how noise, dryness, or smudge levels impact fingerprint ridge estimation.

B. Model Architecture

As shown in Fig 1, For ridge orientation and frequencies estimation, we propose an adaptive CNN architecture. The model consists of convolutional layers, batch normalization, ReLU activations and it is trained with pixel-wise dense supervision. Data augmentation is beneficial for performance under noise and distortion.

Architecture Details:

- Convolutional Layers: 6 layers with 3x3 kernels
- Activation: ReLU
- Optimizer: Adam

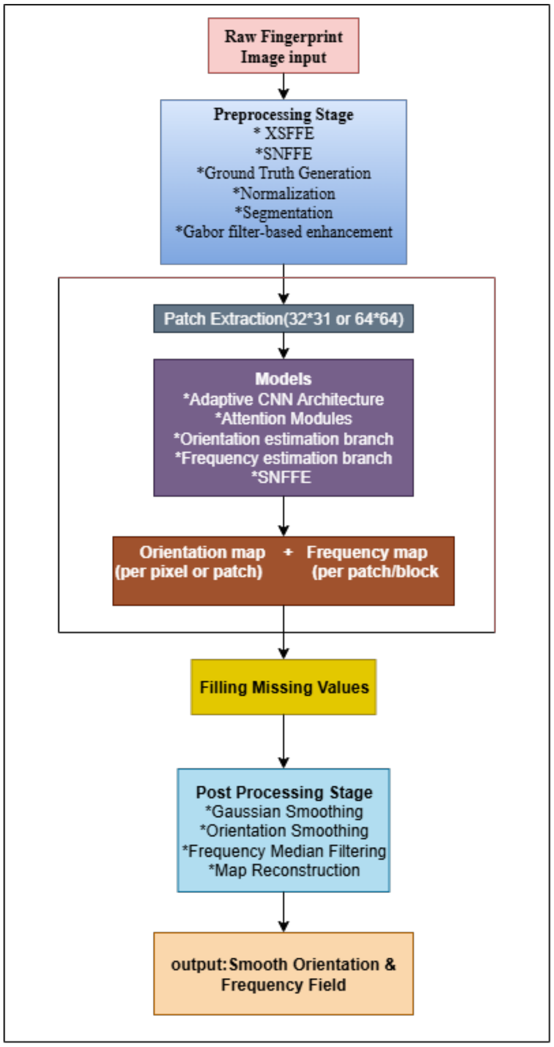

Fig. 1. The system processes raw fingerprint images through preprocessing, patch extraction, and a CNN-based model to estimate orientation and frequency maps, followed by post-processing to generate a smooth orientation and frequency field

- Batch size: 32
- Training Epochs: 100

C. Preprocessing

1) XSFFE – Extended Synthetic Fingerprint Feature Extraction: XSFFE enhances the quality of fingerprint data by generating clean ridge patterns synthetically, or by enhancing to sharpen real images. The CNN is proposed to be able to identify the optimal ridge structures even in the presence of noise or distortion. As shown in Fig 2.

2) SNFFE – Synthetic Normalized Fingerprint Feature Extraction: In Figure 3, SNFFE normalizes a fingerprint image with respect to the variations in brightness, contrast, and ridge sharpness. This enhances the consistency of learning for CNN learning .

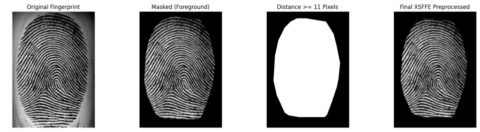

Fig. 2. XSFFE preprocessing pipeline: (a) Original fingerprint image, (b) Foreground mask highlighting ridge regions, (c) Distance transform applied, (d) Cleaned fingerprint output after XSFFE preprocessing.

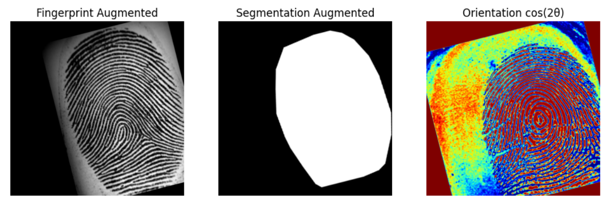

Fig. 3. SNFFE pipeline: Input fingerprint image and segmentation mask are normalized into sharp, consistent ridge patterns for improved model learning.

D. Segmentation

In fingerprint image analysis, segmentation helps in processing only the discriminative portions of a fingerprint. This step separates the actual fingerprint pattern from the background, which is vital for tasks such as orientation estimation, frequency analysis, and minutiae extraction. Segmentation limits processing to relevant areas, which improves both efficiency and accuracy. As shown in Fig 4.

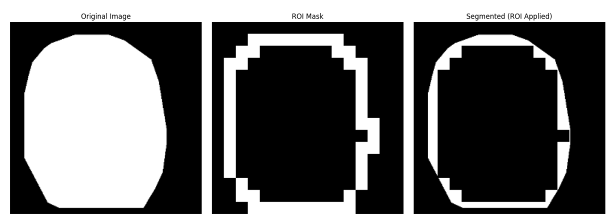

Fig. 4. Segmentation results: (1) Original Image, (2) ROI Mask, (3) Final segmented fingerprint image containing only the region of interest.

E. Orientation and Frequency Estimation

Orientation Estimation: The model predicts the local ridge direction for each pixel, concentrating on the actual fingerprint area while ignoring noisy regions.

Frequency Estimation: Unlike traditional FFT methods, the system estimates ridge frequency by learning local patterns, which makes it robust against smudges and partial prints.

F. Models

1) Adaptive CNN Architecture: An Adaptive CNN architecture is used to adjust feature extraction based on local fingerprint patterns. The network learns both ridge orientation and frequency without depending on predefined rules, making it resilient to noise, distortions, and partial prints.

2) SNFFE: The SNFFE makes a deep neural network that learns how to find the ridge frequency in parts of the fingerprint. This new method solves the limits of old ways of finding the frequency, like using the FFT or the curve fit. The old ways did not work well in dirty or weird spots. The SNFFE uses structure aware learning, which means it gets info about the angle of the ridge in the fingerprint.

3) Orientation Estimation: Orientation estimation focuses solely on the fingerprint area to reduce noise interference. Only sections containing ridge patterns are examined, ensuring accurate computation of local ridge direction .

4) Frequency Estimation: Frequency estimation measures the spacing between consecutive ridges in the fingerprint image. This is extremely important for the preservation of fine details during enhancement and accurate minutiae extraction.

G. Orientation + Frequency Maps

As shown in Fig 5, Orientation and Frequency Maps offer an overview of ridge distribution. The orientation image provides the direction of ridges and the frequency image indicates their spacing. These maps guide the subsequent processes of image enhancement and characteristic extraction.

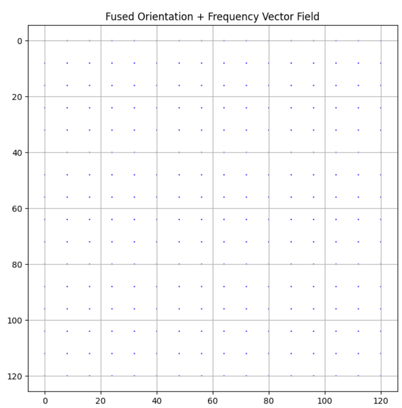

Fig. 5. Fused Orientation + Frequency Vector Field: Arrows represent both ridge direction (orientation) and spacing (frequency), giving a detailed view of local ridge flow.

H. Filling Missing Values

Figure 6, Absent orientation or frequency values may occur in noisy, smudged or partial fingerprint regions. By smart estimation (with the aid of known neighbor values), the smooth flow and sound texture of ridge is prevented for company analysis.

I. Post-Processing

1) Gaussian Smoothing: As shown in Fig 7, Gaussian filtering removes remaining noise and small non-smooth patterns in ridge patterns. This process creates a smoother representation that improves subsequent gradient computations or CNN learning.

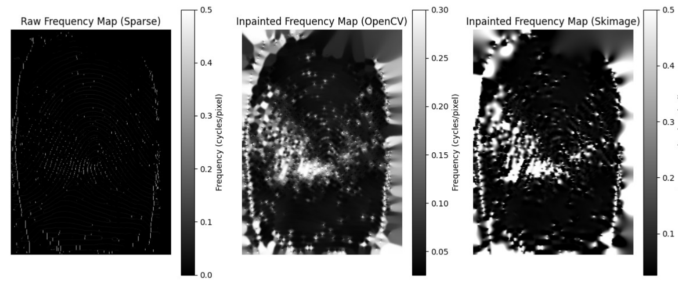

Fig. 6. Filling missing values: (Left) Sparse raw frequency map, (Middle) Inpainted frequency map, (Right) Final inpainted frequency map.

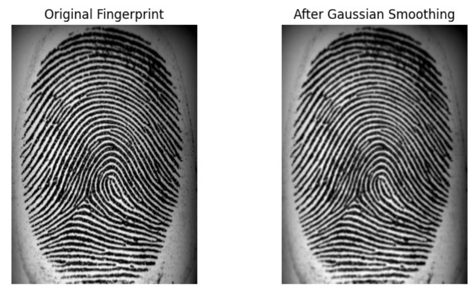

Fig. 7. Fingerprint images before and after Gaussian smoothing. The filter reduces noise and enhances ridge continuity for better feature extraction.

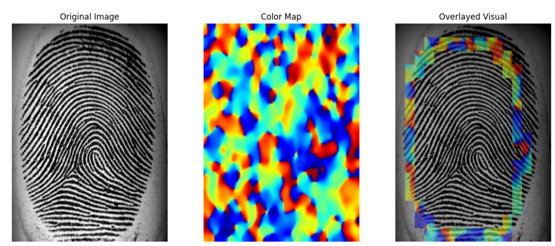

Fig. 8. Overlayed visualization: (1) Raw fingerprint, (2) Regional variations using a color map, (3) Combined overlay for clear visualization of key features.

2) Color Maps and Overlayed Visuals: Color maps and overlayed visuals assist in interpreting fingerprint features by visually showing differences in orientation, frequency, or segmented regions As shown in Fig 8.

3) Map Reconstruction: Map reconstruction repairs incomplete or noisy orientation and frequency maps. By estimating missing or damaged values, the fingerprint representation becomes more consistent and better suited for further analysis .

IV. Evaluation Metrics

Let $I(x, y)$ represent the grayscale intensity of the fingerprint image at pixel coordinates (x, y).

A. Gradient Computation

We calculate the partial derivatives of the image intensity using the Sobel operator:

$$G_x(x, y) = \frac{\partial I(x, y)}{\partial x}$$
$$G_y(x, y) = \frac{\partial I(x, y)}{\partial y}$$

B. Structure Tensor for Orientation Flow

The structure tensor captures the main local ridge direction and improves resistance to noise:

$$G_{xx}(x, y) = G_x(x, y)^2$$
$$G_{yy}(x, y) = G_y(x, y)^2$$
$$G_{xy}(x, y) = G_x(x, y) \cdot G_y(x, y)$$

Averaging over a local area gives the smoothed components $\bar{G}_{xx}, \bar{G}_{yy}, \bar{G}_{xy}$.

C. Local Ridge Orientation

We calculate the local ridge orientation angle, $\theta(x, y)$, as follows:

$$\theta(x, y) = \frac{1}{2} \arctan 2 \left(2 \cdot \bar{G}_{xy}(x, y)\bar{G}_{yy}(x, y)\right) \quad (1)$$

D. Local Ridge Frequency Estimation

1) Windowed Fourier Transform: For a block of size $M \times N$:

$$F(u, v) = e^{-j2\pi\left(\frac{ux}{M} + \frac{vy}{N}\right)} \quad (2)$$

2) Power Spectrum: Compute the magnitude squared of the Fourier Transform, also known as the power spectrum:

$$P(u, v) = |F(u, v)|^2 \quad (3)$$

3) Frequency Calculation: The local ridge frequency $f(x, y)$ comes from the dominant peaks (u_p, v_p) in the power spectrum:

$$f(x, y) = \frac{u_p^2 + v_p^2}{\text{block\_size}} \quad (4)$$

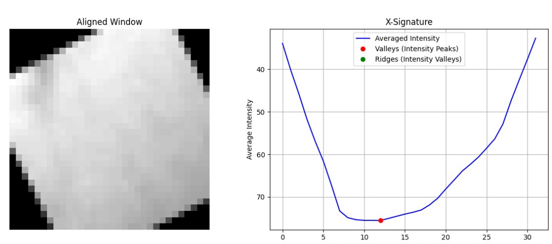

Fig. 9. X-signature analysis

X-signature analysis of a fingerprint window: (Left) Aligned image patch. (Right) X-signature plot showing average intensity along ridge-aligned rows As shown in Fig 9.

V. Result Analysis

A. Accuracy (MAPE) Comparison

Table I proposed SNFFE method achieved the lowest Mean Absolute Percentage Error (MAPE) at 4.58% for good quality images and 5.02% for degraded images. This performance surpassed baseline CNN and regression models.

TABLE I
AVERAGE MAPE ON FFE DATASET (%)

Method	Good	Bad
SNFFE	4.58	5.02
Adaptive CNN (Orientation)	10.5	9.8
Adaptive CNN (Frequency)	12.2	10.5
Orientation Vector Model	11.5	10.2
Frequency Regression Model	11.8	12.9
CNN Classifier	13.0	12.0

B. Execution Time Efficiency

Table II SNFFE runs in 0.012 s, making it suitable for real-time applications. Other methods take between 0.22 s and 0.80 s.

TABLE II
AVERAGE EXECUTION TIME ON FFE (SECONDS)

Method	Average Time (s)
SNFFE	0.012
Adaptive CNN (Orientation)	0.50
Adaptive CNN (Frequency)	0.22
Orientation Vector Model	0.35
Frequency Regression Model	0.80
CNN Classifier	0.37

C. Signature Extraction

We successfully extracted 816 distinct x-signatures from orientation maps. This result confirms the strength of the fused orientation-frequency method in Fig 10.

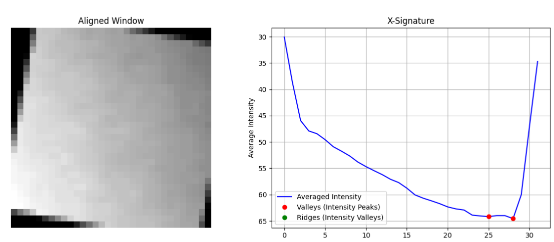

Fig. 10. Fingerprint window aligned along ridge orientation (Left) and corresponding X-signature (Right).

D. Future Directions

- Integrate into real-time fingerprint recognition systems.
- Handle extreme degradation or latent fingerprints.
- Use learned features in end-to-end matching pipelines.
- Explore cross-sensor and cross-population generalization.
- Expand evaluation metrics to PSNR, SSIM, precision/recall, and statistical validation over multiple runs.
- Conduct ablation studies (with and without XSFFE and SNFFE) to measure their contributions.

VI. Conclusion and Future Scope

The works demonstrate that ridge orientation and frequency estimation of image local region is a powerful way in improving fingerprint images quality for deep learning analysis. The aim is to enhance the automated fingerprint identification by extracting ridge features in an efficient manner.

The proposed framework focuses on both **data quality** and **diversity**. A key contribution is the inclusion of the **XSFFE (Extended Synthetic Fingerprint Feature Extraction)** preprocessing module, along with **SNFFE (Synthetic Normalized Fingerprint Feature Extraction)**. These preprocessing steps involve:

- Median filtering and Gaussian smoothing to reduce noise and ensure a consistent ridge flow.
- Foreground masking to isolate the actual fingerprint area.
- Distance-based pixel filtering to eliminate unreliable boundary pixels while keeping high-confidence ridge structures.
- Geometric and photometric augmentations (flips, shifts, rotations, gamma changes, brightness/contrast modifications) to inject variability into the data set for generalization.

A. Key Findings and Strengths

- SNFFE is able to obtain high performance with a **MAPE of 4.58%** for high-quality images and 5.02% for low-quality images.
- **Efficient runtime:** 0.012 second per fingerprint hence applicable to real-time situations as well.
- The combination of XSFFE and SNFFE enhances resilience to noise, smudges, low contrast, partial prints, and distortions.
- The adaptive CNN framework shows strong generalization across various fingerprint conditions because of data augmentation.

B. Limitations

- The current study does not assess **latent fingerprints** or severely degraded prints in detail.
- Testing is limited to one dataset (FFE) and there has been no validation across sensors or population independently.
- Detailed ablation studies to quantify the individual effect of XSFFE and SNFFE were not performed.

C. Future Scope

- Integration into a **complete end-to-end fingerprint recognition pipeline**, which includes minutiae extraction, matching, and classification.
- Extensive testing on **external datasets** to assess performance across different sensors and populations.
- Adding **adversarial robustness** to protect against spoofing or malicious attacks.
- Performing in-depth **ablation studies** to measure the effects of individual preprocessing and CNN components.

In summary, this study shows that combining specific preprocessing methods (XSFFE + SNFFE) with an adaptive CNN creates a highly accurate, robust, and efficient approach for ridge orientation and frequency estimation. This represents a significant advancement in fingerprint biometrics.

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