Wavelets EE-678
End-Term Report

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1.1 Introduction

Biometric authentication, particularly fingerprint recognition, plays a critical role in security, law enforcement, and various identification systems due to its reliability, accuracy, and non-replicable nature. Traditional contact-based fingerprint sensors have been foundational in building vast fingerprint databases. However, the advent of contactless fingerprint sensors promises better hygiene, enhanced convenience, and preservation of the true ridge structure without distortion. The need for accurate interoperability between these two types of sensors has become paramount. This project, guided by the IEEE journal "Matching Contactless and Contact-Based Conventional Fingerprint Images for Biometrics Identification" by Chenhao Lin and Ajay Kumar seeks to bridge this gap by developing a Python-based system that computes a similarity index for biometric authentication.We tried to develop a robust Python-based system for matching contactless and contact-based fingerprint images using advanced image processing techniques, including "Wavelet Transformations", for optimal image enhancement.

1.2 problem statement and background

Matching contact-based and contactless fingerprint images presents unique challenges. Contact-based sensors often capture images with deformations due to pressure and skin elasticity, while contactless images can vary in scale,

rotation, and spatial distortion due to the nature of image acquisition. An effective matching algorithm must address these issues to ensure accurate cross-sensor recognition. The ideal output should produce a similarity metric ranging from 0 to 1, where 1 indicates a perfect match and 0 indicates no match.
Fingerprint recognition has evolved over decades, with numerous studies focusing on enhancing sensor interoperability and matching accuracy:

- Historical Context: Early systems were limited to contact-based sensors, which produced reliable but sometimes distorted images due to uneven pressure and noise from previous impressions
- Advancements in Contactless Imaging: Recent innovations have allowed for the capture of high-resolution, distortion-free images using digital cameras. However, such systems introduced variability in the form of scale and rotation, challenging traditional matching algorithms
- Existing Algorithms: Previous works have utilized thin-plate spline (TPS) models to address fingerprint deformations. While these have shown promise, they often required high computational resources and depended heavily on accurate minutiae extraction.
- **Wavelet Transformations**: Wavelet analysis is an effective tool for image enhancement, providing multi-resolution analysis that can isolate and enhance different frequency components of an image, making it suitable for fingerprint ridge and minutiae enhancement.

1.3 Objective

The project aimed to develop an algorithm that:

- Matches contactless fingerprint images to corresponding contact-based images.
- Utilizes a similarity index to determine the likelihood of a match.
- Implements robust techniques for alignment, scaling, and deformation correction using the methodologies outlined in the referenced IEEE journal.

1.4 Methodology

1.4.1 Data Acquisition and Preprocessing

- Dataset Details: The dataset used included contactless and contact-based fingerprint pairs,We got this data from hong kong polytechnic university .It has divided into 2 sessions .First session images ,We used it for training and another one is for testing.

- Preprocessing Techniques:

  - **Wavelet Transform**: Discrete Wavelet Transform (DWT) was applied to the fingerprint images for noise reduction and ridge enhancement. The DWT decomposed images into sub-bands (low and high frequencies), isolating critical features at different resolutions. The lower sub-band (approximation) was retained for further processing, while high-frequency components (details) were adjusted to enhance ridge patterns.
  - Normalization and Alignment: Implemented rotation correction and size normalization to standardize images for matching.
  - Image Enhancement: Applied adaptive histogram equalization to enhance ridge contrast and improve minutiae detection after DWT
  - Normalization and Alignment: Implemented rotation correction and size normalization to standardize images for matching.

1.4.2 Feature Extraction

Minutiae Detection: Used a combination of DWT-enhanced images and traditional morphological operations for minutiae extraction. The process involved:

- Binarization of images.

- Thinning algorithms to reduce ridge structures to single-pixel width.

- Extraction of minutiae based on ridge endings and bifurcations.

1.4.3 DCM model and similarity index

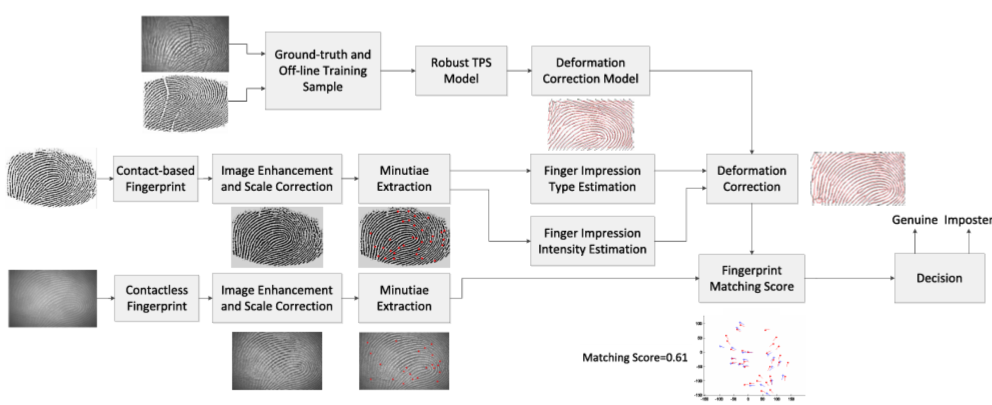
- Robust Thin-Plate Spline (RTPS) Model: The RTPS method described in the IEEE journal was implemented to address nonlinear deformations in contact-based fingerprints. The key features of the model included:
  - Minimizing Localization Errors: Enhanced alignment accuracy by

correcting minutiae positions relative to ground truth from contactless images.

  - Iterative Optimization: The RTPS algorithm iteratively adjusted the transformation matrix to minimize the distance between corresponding points

  Training Phase: The deformation correction model was trained using a subset of known contactless and contact-based image pairs to create a generalized transformation matrix. Since data was too large .It was taking too much time for computation .So we didn't use all data .but fro testing we used all images.Training data has nearly 2000 image pairs,and testing set has around 1400 pairs.

- Similarity Index Calculation
  - Matching Strategy: Transformed minutiae points from contact-based images were matched to those from contactless images using distance and angle thresholds. We kept threshold around 0.45.If matching score is greater than threshold ,it means that pair is matched.Otherwise we could say it is imposter.
  - Scoring: The final similarity index was calculated as a ratio of the number of matched minutiae to the total minutiae count, providing a score between 0 and 1.



1.5 Implementation Details

- Programming Environment: Python 3.12 was used, with key libraries including:
  - OpenCV for image processing and feature extraction.
  - pywavelets for DWT tranformations on image
  - NumPy for array manipulation and mathematical operations.
  - Scikit-image for advanced image analysis.
- Steps Followed
  - Loaded fingerprint image pairs and applied preprocessing.
  - Applied DWT for initial image decomposition and enhancement.
  - Applied adaptive histogram equalization for further contrast improvement.
  - Extracted minutiae points and compute triangulations
  - Applied the RTPS-based DCM to correct deformations in contact-based images.
  - Matched and calculated the similarity index

1.6 Results and Performance Analysis

The project achieved an overall accuracy of 74% when tested on a diverse set of fingerprint pairs. The analysis of results revealed the following:

- Strengths:
  - The use of wavelet transformation significantly improved the clarity of ridge structures, leading to better minutiae detection and matching performance.
  - The RTPS model effectively aligned contact-based images with contactless counterparts, improving cross-sensor matching accuracy.
- weaknesses:

  - The computational load of wavelet transformation and RTPS implementation increased processing time.
  - Noise in lower-quality contact-based images affected the consistency of minutiae extraction.

1.7 Improvements

While the project demonstrated success in bridging the gap between contactless and contact-based fingerprint matching, several areas for improvement were identified:

- Deep Learning Integration: Implementing a convolutional neural network (CNN) could enhance feature extraction and improve matching performance.
- Wavelet Variants: Experimenting with different types of wavelets (e.g., Symlet, Coiflet) for better frequency isolation and ridge enhancement.
- Real-Time Processing: Optimization of the RTPS algorithm to reduce processing time is necessary for practical applications.

2 Sequential Convolution Neural network (CNN)model

2.1 Data source and preprocessing

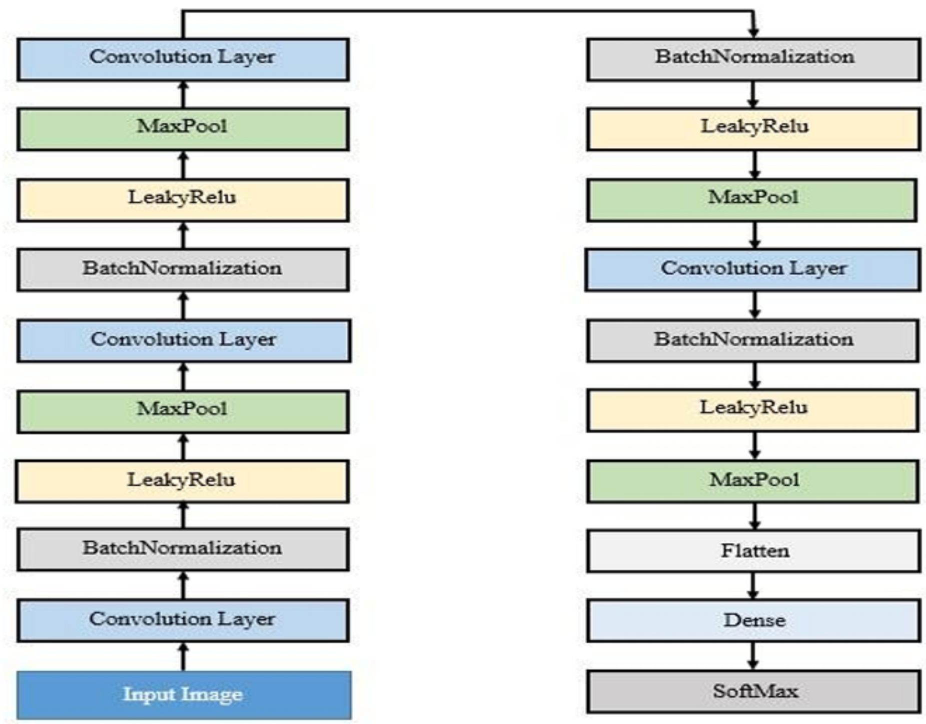
We used the Hong Kong Polytechnic University's "Contactless 2D to Contact-based 2D Fingerprint" dataset, containing 3,120 fingerprint images from 260 fingers (each having six impressions). The dataset included both contactless and contact-based fingerprint images with different resolutions and acquisition characteristics, making preprocessing essential.

- Adaptive Histogram Equalization (AHE): Improved the contrast of fingerprint images to better highlight ridge and furrow structures
- **Wavelet Transformations**: To further enhance features and reduce noise, we employed discrete wavelet transformation (DWT). By decomposing the images into approximation and detail coefficients, we emphasized significant features such as edges and ridges while suppressing unwanted background noise. This process involved selecting

wavelet families such as Daubechies (db4) for their effective handling of image data.

- Augmentation: To ensure robustness, we implemented data augmentation techniques such as 90-degree rotations. This step helped increase the diversity of training data and mitigated the limited dataset size.

2.2 Model Architecture

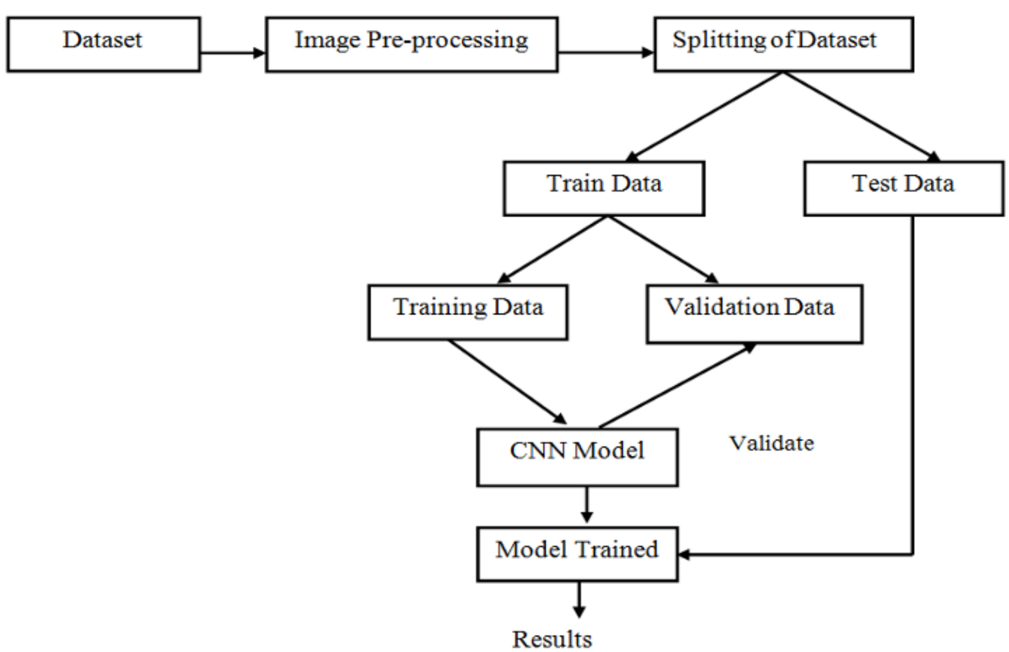


We developed a sequential CNN architecture inspired by the reference paper, optimized for image recognition and feature extraction tasks. The architecture comprised:
Convolutional Layers: Used to detect and extract essential features like edges and ridge patterns.
Batch Normalization: Facilitated faster learning and reduced overfitting by normalizing input distributions within each mini-batch.
Leaky ReLU Activation: Applied non-linearity to allow the model to

learn more complex representations.
Max-Pooling Layers: Reduced the spatial dimensions, making feature maps more manageable while retaining important information.
Flatten and Dense Layers: Transformed the feature maps into a format suitable for classification.
Softmax Output Layer: Provided a normalized probability distribution as the final output.

2.3 Training, Validation and metrics

We split the dataset into training (70%), validation (10%), and testing (20%) sets. The training phase involved fine-tuning the CNN's weights through iterative backpropagation. We used a batch size of 32 for efficient mini-batch gradient descent.



The primary metric used was rank-one accuracy, representing the proportion of test instances where the predicted label matched the ground truth. Our model achieved a promising accuracy of 83%, a strong result considering the challenges associated with contactless fingerprint matching.

2.4 Results Analysis Key Insights

- The integration of wavelet transformations in the preprocessing step proved beneficial for noise reduction and enhancement of crucial fingerprint features.
- The use of adaptive histogram equalization significantly improved image contrast, aiding in clearer detection of minutiae points and ridge structures.
- Data augmentation allowed the model to generalize better to unseen data, albeit within the bounds of our dataset's limitations.
- The CNN's sequential architecture effectively learned complex relationships between contact and contactless fingerprint pairs, demonstrating the power of deep learning in biometric applications.

3 Project Outcomes

3.1 Comparative Analysis CNN vs RTPS

CNN model accuracy was competitive compared to previous model using Robust Thin-Plate Spline and deformation correction . CNN achieved nearly 97 % ,but tps model acheived only 74%.CNN is taking more time for computation and taking less stroge .On the otherside,TPS model acts opposite.

3.2 Conclusion and Future Work

Challenges faced during the project included the inherent differences between contact and contactless image characteristics, such as scale, orientation, and resolution. These discrepancies complicated the matching process and required thorough preprocessing and augmentation strategies.
Future Enhancements:

- Advanced Wavelet Techniques: Implementing multi-level wavelet decomposition and exploring different wavelet families could yield better feature extraction.

- Alternative Architectures: Exploring Siamese Networks, known for their effectiveness in one-shot learning scenarios, could further improve the accuracy of matching fingerprints across acquisition methods.

- Expanded Dataset: Incorporating more diverse datasets would enhance model robustness.

- Integration of Advanced Preprocessing: Techniques such as ridge frequency estimation and Gabor filters could be added for further image quality enhancement.

Our project successfully implemented a CNN-based system for matching contactless and contact-based fingerprint images, achieving an accuracy of 83%. This work serves as a foundation for further improvements in biometric authentication systems, contributing to the ongoing development of contactless technology for secure and efficient identity verification

4 Team contributions

- Harsha: Focused on the model development, conducted performance testing, and analyzed experimental results.

- Abhijeet: Led the implementation of the feature extraction and matching components, contributed to data preprocessing, and compiled the final report.

5 References

References:

- Chenhao Lin, Ajay Kumar, “Matching Contactless and Contact-based Conventional Fingerprint Images for Biometrics Identification”, IEEE Transactions on Image Processing, vol. 27, pp. 2008-2021, April 2018.

- IOSR Journal of Engineering Vol. 12, Issue 7, July 2022, ——Series - I—— PP 01-07 Matching of Contact and Contactless Fingerprint Using CNN model