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FEATURE EXTRACTION TECHNIQUES FOR FINGERPRINT RECOGNITION

BY

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Abstract

The feature extraction involves the process of converting original data into a set of numerical features that can be processed by machine learning algorithms while conserving the significant information from the original data. It's a key phase in data preprocessing, specially for intricate datasets, as it can make simpler the data, decrease dimensionality, and improve model performance. In fingerprint recognition systems, the feature extraction remains a very important stage because it reduces the complexity of fingerprint data, enables effective and efficient matching, and enhances the overall performance and accuracy of the system. This process transforms raw fingerprint images into a set of distinctive and stable features, such as minutiae points (ridge endings and bifurcations) and global patterns, which are then used for identification and verification. The study conducts a literature on feature extraction techniques for fingerprint recognition system. Different algorithms were mentioned with associated challenges and further future areas of improvement were suggested.

Introduction

A fingerprint is the pattern of ridges and valleys present on the surface of a fingertip, which is unique, permanent, and can be used for reliable individual identification due to its distinctiveness and immutability over time (Askarin et al., 2025). Fingerprints as “an impression made by the papillary ridges on the ends of the fingers and thumbs,” noting their infallible value in identification since no two are alike and they remain unchanged over time Britannica (2025). Fingerprint refers to the pattern of friction ridges and valleys on the surface of a finger, which remains permanent throughout a person’s life and is unique to each individual, making it a reliable biometric trait for personal identification and verification.(Reena, Gunjan, Aditya, & Manu, 2024). These ridges are the raised portions of the skin of hands and feet. There exist several advantages that make fingerprint recognition methods popular.

Due to their consistency and reliability in biometric feature identification, they are most widely used for biometric recognition systems. Fingerprints can be considered a crucial and dominant trait in the field of biometrics because of their high security prominence, reliability, low cost, and acceptability (Upendra et al., 2023). As fingerprint identification systems and fingerprint systems deployments are highly in demand, numerous challenges are arising in every phase of the system, which includes feature extraction, matching of features, classification of fingerprints, and enhancements of the fingerprint image. Fingerprint recognition has been a stalwart of biometric authentication systems for decades, owing to its high accuracy, uniqueness, and resistance to forgery. Fingerprint recognition finds applications in numerous fields in numerous applications, from secure access control systems and mobile phones to forensic examination and identity verification in numerous security-sensitive environments (Moolla et al, 2021). In the past, they used fingerprints to recognize a person in law enforcement. Fingerprints as reproductions of the fingertip epidermis pattern—interleaved ridges and valleys highlighting their uniqueness, permanence, and biometric relevance (Donida Labati & Scotti, 2021**)**. After that, they used fingerprints for criminal investigation and

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forensic purposes. It is continuous until now. A fingerprint is an impression made by a person's fingertip on a surface (Perichappan and Sasubilli,2017).

Digital images are one of the most important and widely used data types. An example of this is the human fingerprint, used in important applications such as banking Systems, person identification systems, and many other important computer applications (Ali et al, 2016). It is better to reject degraded images during training so that the performance of the fingerprint recognition system can be maintained. Another issue in fingerprint recognition systems is the use of multiple sensors. Different sensors interpret and represent fingerprint images differently (Fernandez et al., 2015). Changing the sensors may affect the performance of the fingerprint recognition systems. It will be a good idea to represent fingerprint images under a common exchange format. Another way by which this problem can be avoided is to normalize the raw data and extracted features. Apart from advantages of fingerprint recognition systems, they are also targets of attacks. Unfortunately, fake input to biometric recognition systems proved to be successful. Matching score (threshold value) is a pivotal element in fingerprint recognition systems. Additional challenges include matching fingerprints that are affected by plastic distortions. Classification method for efficient search of fingerprints in a fingerprint database is also the biggest challenge (Fernandez et al., 2015). Automated fingerprint recognition systems have certain pitfalls. It may sometimes require not only a fingerprint but also a valid PIN, which can be more difficult to use than traditional systems. Sometimes false rejection may happen when the fingerprint recognition system fails to register someone's fingerprint. This is called type I error (Kute& Kumar, 2014)..

Sometimes, a fingerprint recognition system may identify the wrong person during the authentication process, leading to unauthorized access. This is called type II error (Kute& Kumar, 2014). Hence, a good fingerprint recognition system should overcome type I and type II errors, and it should also be accurate. Performance of any fingerprint recognition system heavily relies on the quality of fingerprint image. Quality of a fingerprint image is governed by factors such as skin conditions, sensor conditions, poor user cooperation, etc. Few factors can be avoided, whereas few vary over time. Hence, lack of robustness is an important issue in fingerprint recognition systems (Singh &Yashika, 2014). Fingerprints cannot change unless there is a physical disturbance, such as accidents or work in an industry with caustic or hot materials, which may damage fingerprints (Mikhail, Dremin &Leshko, 2013). Fingerprint has been used since the eighth century AD history during China's Tang dynasty in clay to describe, serving as a kind of signature in business contracts and law enforcement cases (Glaeser, Sonderegger, and Peter, 2012). One biggest advantages is that it is very well accepted in the legal community. It is the cost-effective, quick, reliable, and most convenient way to identify a person. Fingerprint recognition is widely accepted as a highly accurate method of authentication since the chance of two people having identical fingerprints is scarce (Davis, 2008). Each person has a unique fingerprint (FP) (Sudiro et al, 2007) that does not repeat and does not resemble any other fingerprint or that of any other person. The fingerprint usually consists of several objects, varying from one person to another.

LITERATURE REVIEW

Feature Extraction Techniques for Fingerprint Recognition

Feature extraction in biometric systems aims to isolate and represent the most relevant characteristics of an individual's biometric trait to facilitate matching, while minimizing intra-class variability and maximizing inter-class separability. (Yang, Sun, & Tan,2024). Feature extraction is the process of reducing the dimensionality of data by selecting or transforming relevant information (features) from raw data to make pattern recognition and classification more efficient and accurate. In *biometric systems* like fingerprint recognition, feature extraction identifies unique characteristics (e.g., ridges, minutiae points, texture patterns) that can distinguish one individual from another. Feature extraction is a process of transforming input data into a reduced set of features that preserves important information, allowing the data to be represented compactly and discriminatively for pattern recognition tasks (Jain, Ross, & Prabhakar, 2004). Feature extraction is the process of deriving discriminatory information from raw biometric data to facilitate accurate identification or verification (Upe, Ezugwu, & Onwubolu, 2023). Feature extraction transforms raw data into a set of informative, non-redundant features, often leveraging deep models to automatically learn hierarchical representations that enhance classification performance. (Tandon & Namboodiri,2022).

Types of Feature Extraction

Feature extraction is a crucial step in biometric and pattern recognition systems, transforming raw data into a compact, informative representation that facilitates accurate classification and matching (Jain et al., 2004). Several types of feature extraction techniques have been developed to address different biometric traits and data characteristics.

- **(i)** **Minutiae-based feature extraction** focuses on identifying distinct local ridge characteristics, such as ridge endings and bifurcations, which are especially important in fingerprint recognition. This approach remains one of the most widely adopted due to its high discriminative power (Malathi & Radha, 2011).
- **(ii)** **Texture-based feature extraction** captures ridge flow, frequency, and local patterns using methods like Local Binary Patterns (LBP), Gabor filters, and wavelet transforms. These techniques are effective in enhancing the robustness of biometric systems, particularly when the minutiae data is of poor quality (Kute & Kumar, 2014).
- **(iii)** **Frequency-domain or transform-based feature extraction** applies mathematical transforms, such as Fourier Transform, Discrete Cosine Transform (DCT), or wavelet transform, to convert spatial data into frequency domains, revealing additional discriminative features. This method is commonly applied in fingerprint, face, and speech recognition tasks (Liu, Yin, & Zhang, 2010).
- **(iv)** **Geometric or structural feature extraction** uses the overall layout or shape descriptors, including orientation fields and singular points (core and delta points), to provide a global representation of the biometric trait (Upe, Ezugwu, & Onwubolu, 2023).
- **(v)** **Statistical feature extraction** leverages statistical properties, such as mean, variance, and correlation of pixel intensities, to describe the data. This method is often combined with other approaches to improve performance.
- **(vi)** **Deep learning-based feature extraction** represents a modern advancement where neural networks, particularly Convolutional Neural Networks (CNNs) and transformers, automatically learn hierarchical feature representations from raw data. These models have shown superior performance in recent biometric systems (Tandon & Namboodiri, 2022). Finally, **hybrid feature extraction** combines multiple methods—such as minutiae with texture or deep features—to enhance system accuracy and robustness (Jain et al., 2004).

Related Works

Askarin et al. (2025) propose a U-Net-Based Fingerprint Enhancement for 3D Recognition. A 3D point cloud flattening method, adapted from an existing 3D fingerprint unwrapping approach, which we use to convert 3D fingerprints into 2D gray-scale fingerprint images. Subsequently, we present the proposed method aimed at enhancing these generated images. The fingerprint impressions of the first 210 subjects in session 1 of this dataset were used for training the model (Dataset A), and the fingerprint impressions of subjects 211 to 300 (Dataset B) were used for testing in the first experiment. Session 2 of this database has 200 subjects (Dataset C), which were used for testing in the second experiment. In both sessions, each subject had six 3D fingerprint impressions, which were represented in 3D point cloud format with the dimensions of 900 by 1400 points. For each point cloud impression, two corresponding contactless 2D images were also available, with dimensions of 1536 by 2048, which

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were captured with different illuminations. Our future work will focus on resolving misaligned ridge and valley patterns in the enhanced images of the patch-based method, as this refinement has the potential to significantly improve performance and will be our primary research focus moving forward.

Linglong et al (2024) developed on Fingerprint Recognition Algorithm. The fingerprint image is scanned from left to right and from top to bottom in order to scan the points on the entire image, and then the points on the image are judged to achieve fingerprint feature point extraction. Then, the fingerprint image is preprocessed and feature extracted, and the center point of the fingerprint, the direction field of the fingerprint image, and the coordinates of the feature point are obtained. The reference direction of the fingerprint is extracted. After the reference point and the reference direction of the fingerprint are determined, the characteristic information of the fingerprint is modified and the characteristic information is expressed in polar coordinates. The template and the feature information of the input image are sorted in the direction according to the direction of increasing polar angle, and the feature information is connected in series. If the matching degree of feature points is greater than the preset value, it is considered that the two fingerprints are matched successfully. It can be seen from the experimental results that the two fingerprint images are loaded, the feature point map and the smooth processing map are extracted after pre-processing, and the feature point matching degree is calculated. It was judged that the two fingerprint images are from the same fingerprint.

Reena et al (2024) examined Fingerprint recognition using a convolutional neural network with inversion and augmented techniques. Deep neural network architectures are used with proposed inversion methods and multi-augmentation methods to classify the samples of fingerprints for personnel identification and verification. Pre-trained deep convolutional models like VGG16, VGG19, ResNet50, and InceptionV3 are fine-tuned with new processed fingerprint images for feature extraction and classification. The simulation results have been obtained with different optimizers, and it has been observed that the VGG 19 model exhibits the accuracies of 88 % and 93 % with inversion and multi-augmentation approaches, respectively. Whereas, VGG16 model exhibits 93 % with inversion approach and 97 % with multi augmentation approach. Thus, the proposed approach exhibits the accuracy up to 97 % with the VGG16 model, which is significantly higher than that of any other model with the same dataset FVC2000_DB4. Proposed approaches can also be validated on other datasets than FVC2000-DB4 for more generalization.

Pranav, Sahil, and Sandeep (2024) proposed Recognition of Fingerprint Biometric Verification System Using Deep Learning Model. This paper provides a comparative analysis of different deep learning models that enhance the performance of fingerprint recognition. It follows some key phases like data analysis, data pre-processing, classification, and feature extraction also evaluates the performance according to accuracy measures. This research presents the results of a YOLO-based fingerprint detection approach that outperforms competing methods. Before improving the YOLO network structure, a fingerprint feature dataset was created, which included four thousand annotated fingerprint photos. The fingerprint feature points were densely distributed, and the dataset was rather small. Findings demonstrate that while the detection speed remains largely similar, the mAP0.5 value increases from 93.0% to 97.4% when compared to the FP-YOLO (Fingerprint- YOLO). Model of the other models. FP-YOLO stands out with an exceptional accuracy achievement of 97.4%, outperforming its counterparts by a significant margin.

Nuno, José, and Alexandre (2024) examined Fingerprint Recognition in Forensic Scenarios. This work proposed an efficient methodology that can be applied in real time to reduce the manual work in crime scene investigations that consumes time and human resources. The proposed methodology includes four steps: (i) image pre-processing using oriented Gabor filters; (ii) the extraction of minutiae using a variant of the Crossing Numbers method which include a novel ROI definition through convex hull and erosion followed by replacing two or more very close minutiae with an average minutiae; (iii) the creation of a model that represents each minutia through the characteristics of a set of polygons including neighbouring minutiae; (iv) the individual search of a match for each minutia in different images

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using metrics on the absolute and relative errors. A random set of 125 images from the FVC2000 DB1 database was chosen, which resulted in 125 genuine comparisons and 7154 imposter matches. An average of 23 minutiae (represented by polygons) were registered. Also, simple features of each polygon were chosen to allow the outlined objectives to be achieved, without increasing the computational effort, but there is the possibility of exploring other features.

Hydr, Mohammed, and Mohammed (2024) stated Automatic human identification using fingerprint images based on Gabor filter and SIFT features fusion. This article proposed a hybrid biometric system that integrates the Gabor filter and scale-invariant feature transform features and then uses support vector machine and K-nearest neighbors as classifiers, aiming to notably enhance authentication systems by mitigating issues seen in single-method biometric systems. Also, principal component analysis is used to reduce dimensions and eliminate redundancy. In this article, the famous database FVC2004 is used. SVM classification were gained by combining the Gabor filter and SIFT, with a precision of 99.6% and the execution time of 6.4 s, the Gabor filter and SIFT with PCA with a precision of 100% and the execution time of 3.4 s, the K_NN classification were obtained by fusing the Gabor filter and SIFT, with a precision of 99.3% and a runtime execution time of 6.3 s, K_NN classification were obtained by mixing the Gabor filter and SIFT with PCA with a precision of 100% while the execution time was 3.8 s. Also, it was noticeable that the SVM classification proved its efficiency over the K_NN classification. Hussein and Zainab (2024) investigated Fingerprint Identification System based on VGG, CNN, and ResNet Techniques. This study compares three different pre-trained deep learning models specifically designed for fingerprint identification. The first model uses Convolutional Neural Network (CNN), the second includes Residual Network (ResNet), and the third employs the Visual Geometry Group (VGG) approach. The subsequent comparative assessment reveals the CNN-based model's superior performance, with an impressive F1 score of 96.5%. In contrast, the ResNet and VGG models achieve F1 scores of 94.3% and 92.11%, respectively. These findings highlight the CNN model's ability to accurately identify fingerprints. Furthermore, a comparative analysis is performed between the obtained results and those reported in recent studies using the same dataset.

Sajidah and Abdul-Wahab (2024) proposed Fingerprint Recognition Revolutionized: Harnessing the Power of Deep Convolutional Neural Networks. Our technique uses Deep Convolutional Neural Networks to address these difficulties. Our ensemble model uses ResNet101, ResNet50, AlexNet, and two exclusive models to improve fingerprint analysis. This ensemble technique uses a softmax layer to combine model predictions and revolutionize biometric security. This integration uses ResNet models' deep learning and AlexNet's efficient image processing to manage fingerprint data's intricacies, including IDs, finger numbers, and gender. The ensemble model in our study performed SubjectID identification, FingerNum categorization, and Gender recognition with 99.67% to 99.95% accuracy. Our ensemble model, which used various deep learning architectures, outperformed standard fingerprint analysis methods.

Rumana, Masudul, and Stephanie (2024) examined Longitudinal Study on fingerprint Recognition in Infants, Toddlers, and Children. However, these studies were conducted on a small dataset over a shorter period with limited diversity; further evaluation of their finding is essential. This study assessed the effectiveness of a high-resolution contactless scanner in a controlled, diverse longitudinal dataset of children (0-15 years). Our results indicate that infants can be enrolled at five days old and reliably recognized after two months with a TAR= 100% @ FAR = 0.1%, and children aged 4-15 years can be recognized after one year with a TAR= 98.72% @ FAR = 0.1%. One limitation of our study is the relatively small dataset of young children, suggesting the need for further research to validate our findings for this demographic. Future work will involve collecting more longitudinal data from additional subjects and examining factors like age at enrollment, demography, the time gap between enrollment and authentication, and image quality, using the Linear Mixed Effect model to understand their impact on match scores.
Yunfei et al (2024) investigated Convolutional Neural Network and Ensemble Learning-Based Unmanned Aerial Vehicles Radio Frequency Fingerprinting Identification. This paper develops an ensemble learning ADS-B radio signal recognition framework. To extract features from different signal segments, a method merging end-to-end and

non-end-to-end data processing is approached in a convolutional neural network. Subsequently, these features are fused through EL to enhance the robustness and generalizability of the identification system. Finally, the proposed framework's effectiveness is evaluated using collected ADS-B data. The experimental results indicate that the recognition accuracy of the proposed ELWAM-CNN method can reach up to 97.43% and has better performance at different signal-to-noise ratios compared to existing methods using machine learning.

Deep et al (2023) proposed Enhancing Fingerprint Liveness Detection Accuracy Using Deep Learning: A Comprehensive Study and Novel Approach. The proposed methodology relies on an attention model and ResNet convolutions. Spatial attention (SA) and channel attention (CA) models were used sequentially to enhance feature learning. A three-fold sequential attention model is used along with five convolution learning layers. The method's performances have been tested across different pooling strategies, such as Max, Average, and Stochastic, over the LivDet-2021 dataset. Comparisons against different state-of-the-art variants of Convolutional Neural Networks, such as DenseNet121, VGG19, InceptionV3, and conventional ResNet50, have been carried out. In particular, tests have been aimed at assessing ResNet34 and ResNet50 models on feature extraction by further enhancing the sequential attention model. A Multilayer Perceptron (MLP) classifier used alongside a fully connected layer returns the ultimate prediction of the entire stack. The proposed methodology uses a unique approach to see the realness of figure print from pictures, as dual attention-based Resnet50 architecture has achieved 97.78% remarkable accuracy on the LivDet fingerprint dataset. The proposed methodology is superior to other deep learning convolution models, such as Xception, InceptionV3, VGG19, DenseNet121, and InceptionV3, with around 0.7% accuracy. The proposed study is also planned to be improved by integrating Explainable AI to interpret the prediction of the proposed deep learning model.

Abdoul et al (2023) examined Fingerprint Recognition Using a Transfer Learning Method. Fingerprint image acquisition, feature extraction, and comparison or matching. Firstly, we use non-contact fingerprint images for training the recognition model to allow the developed system to work without contact. Secondly, we used a database of nineteen individuals, each having fifteen fingerprint images acquired without contact. To perform the transfer learning, we have exploited the MobileNets model while adapting its architecture to the new task of contactless fingerprint classification. After training the new model, we performed its evaluation through a confusion matrix. This evaluation reveals that the developed method confuses one individual out of 19, i.e., a confusion rate of 5.26%. This rate testifies to the efficiency of the method used for non-contact fingerprint recognition. After evaluating the results, we can say that this transfer learning method is effective for the identification of fingerprint images.

Almas et al (2023) investigated fingerprint recognition systems for Person Identification Using Termination and Bifurcation Minutiae. Two major categories of minutiae, termination & bifurcation, are used here. The system is activated through an artificial neural network. The proposed approach for feature level provides a better result. The recognition rate is increased & the error rate is decreased with the help of this system. The recognition rate of this proposed method of fingerprint recognition system using neural network is 90.06%. The system is giving an overall accuracy of 90.06 % with FAR and FRR of 1.24% and 6.09%. In future studies, we can use this fingerprint trait in a multimodal biometric system to enhance the accuracy rate.

Challenges and Limitations of Feature Extraction Techniques for Fingerprint Recognition

Feature extraction methods for fingerprint recognition contend with several significant limitrations and challenges that affect the dependability and recognition rate of fingerprint biometric systems. One of the predorminant issues is the poor quality of fingerprint images, which may be degraded by noise, smudges, or low contrast due to dry or oily skin. These limitations make it hard to accurately find and obtain important features such as minutiae points and ridge patterns. Also,, fingerprint impressions are often subject to non-linear distortions caused by variations in pressure elasticity of skin, and finger positioning, which can change the geometric structure of the fingerprint and cut down the consistency across scans. Partial fingerprints, generally obtained from small sensors in mobile devices

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or through under pressure captures, produce limited information and further thwart the process of extractions. Furthermore, intra-class variability differences in the same person's fingerprint over time and inter-class similarity sameness between prints of different persons pose difficulties in distinguishing users. Several advanced extraction techniques, like or Neural Networks or Gabor filters, are computationally intensive, making real-time processing on low-resource devices a challenge. In addition, obtained features can be sensitive to noise and may include false minutiae or artifacts that affect matching performance. The lack of standardized feature extraction procedures also reduces interoperability between systems, and convectional approaches often struggle to obtain meaningful global or high-level features from fingerprint images. Finally, the susceptibility of fingerprint systems to spoofing attacks using artificial fingerprints highlights the necessity for more secure and robust feature extraction methods.

Conclusion

Feature extraction remains an important component in the accuracy and robustness of fingerprint recognition systems. Several techniques including minutiae-based, ridge-based, and texture-based techniques, have been extensively explored, each with unique strengths and limitations. Minutiae-based approaches, while highly accurate, often require high-quality images and are sensitive to noise and distortion. Ridge and texture-based methods offer complementary features and improve performance in challenging conditions. Current development in machine learning and deep learning have also improved the efficiency and adaptability of feature extraction processes. Overall, continuous study into hybrid methods and improved preprocessing techniques is necesssary for incapacitating present limitations or challenges and achieving more dependable fingerprint recognition ssytem in real-world applications.

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