

Sparse Representation-Based Fingerprint Compression

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Abstract:- Fingerprint compression is a crucial aspect of biometric systems, designed to reduce memory requirements while preserving the essential features necessary for accurate recognition. Compression can be either lossy, where some image degradation occurs, or lossless, which retains the original quality. Traditional compression methods like JPEG (using Discrete Cosine Transform) and JPEG 2000 (using Discrete Wavelet Transform) fall under lossy frequency domain techniques. However, these methods often fail to balance high compression ratios with quality retention. To address this, a spatial domain technique based on sparse representation is proposed. This method divides the image into 20x20 pixel patches and constructs a dictionary to eliminate redundancy. Patch values exceeding a predefined threshold are retained in the dictionary, while others are discarded. Performance metrics such as PSNR, MSE, and compression ratio demonstrate significant improvements over classical methods. Fingerprint images, crucial in legal and forensic investigations, often contain vast amounts of data. These images are rarely perfect and can suffer from degradation due to variations in skin texture or impression conditions. Image enhancement techniques are applied to improve minutiae detection reliability before compression. Sparse representation-based compression involves creating a dictionary of predefined fingerprint patches, dividing the image into smaller blocks, and calculating sparse coefficients for each block. These coefficients are then quantized and encoded. Experimental results on various fingerprint datasets reveal that this method is more efficient than other compression techniques, effectively preserving critical minutiae features even after compression.

Key-Words: Fingerprint compression, Biometric systems, Sparse representation, Lossy compression, Dictionary construction, Image enhancement, Minutiae detection, Compression ratio, DWT (Discrete Wavelet Transform), Reliability.

Received: March 16, 2024. Revised: March 6, 2025. Accepted: April 10, 2025. Published: May 8, 2025.

1 Introduction

Biometric recognition utilizes various methods such as fingerprint, iris, and facial recognition to enhance security monitoring. Among these, fingerprint recognition is particularly effective due to its uniqueness and reliability. However, as fingerprint databases expand, efficient memory utilization and fast data access become essential. Image compression plays a crucial role in managing large data volumes by reducing fingerprint image size while preserving critical features.

Traditional compression techniques like Discrete Cosine Transform-based JPEG (DCT-JPEG) and Discrete Wavelet Transform-based JPEG2000 (DWT-JPEG2000) are widely used but have limitations in quality retention and memory efficiency. These frequency-domain lossy compression methods introduce some quality degradation. To address these challenges, propose a novel spatial domain sparse representation-based compression method for fingerprint images. This approach analyzes pixel gray-level values directly in the spatial domain, ensuring high compression efficiency while preserving essential fingerprint details.

The compression process begins by selecting a fingerprint image from a database and applying a threshold to retain only significant pixels while discarding the rest. The sparse-represented image is then divided into 20×20 patches, which are optimized using a minimization problem (MP) method to reduce reconstruction errors. Huffman coding and quantization are then applied to generate a binary stream for the compressed image. The effectiveness of this method is evaluated using quality metrics such as Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR), demonstrating superior compression ratios and image quality compared to DCT-JPEG and DWT-JPEG2000.

Fingerprint recognition has been a cornerstone of biometric identification for over a century, serving critical roles in forensic science, law enforcement, and commercial security systems. As fingerprint databases grow, efficient compression techniques become necessary to reduce storage demands and enhance identification speed. Additionally, since fingerprint images are frequently

transmitted between agencies, compression ensures secure and efficient data exchange.

Various image compression standards, including JPEG, JPEG 2000, and Wavelet Scalar Quantization (WSQ), have been developed. While JPEG and JPEG 2000 are general-purpose, WSQ is specifically designed for fingerprint compression and is widely adopted in law enforcement. Inspired by WSQ, several wavelet packet-based compression methods have emerged, yet they struggle with degraded or noisy fingerprint images. Variability in skin conditions and impression quality often introduces noise, which can compromise minutiae extraction and recognition accuracy.

To mitigate these challenges, robust fingerprint enhancement techniques are required before compression. Our proposed method constructs a base matrix to represent fingerprint image features, serving as a dictionary where each column functions as an "atom" (a fundamental feature). The fingerprint is divided into small patches, and sparse representation is applied to extract coefficient values from these patches. These coefficients are then quantized and encoded using lossless compression techniques. This approach not only improves compression efficiency but also preserves key fingerprint characteristics crucial for recognition.

Biometric recognition, especially fingerprint identification, is integral to modern security frameworks. The uniqueness and permanence of biometric traits make them a reliable means of identity verification. However, fingerprint images can suffer from noise and degradation, affecting recognition performance. To counter these issues, robust image enhancement and feature extraction techniques are crucial. We introduce a sparse representation-based compression method that utilizes a dictionary model to encode fingerprint patches, ensuring high compression efficiency while minimizing quality loss. Furthermore, this technique facilitates feature-level fusion in multimodal biometric systems by integrating multiple biometric traits (e.g., fingerprint, iris, face), thereby improving recognition accuracy and addressing challenges like non-universality and noisy data.

By leveraging sparse representation for both compression and feature fusion, our approach effectively addresses technical fingerprint

compression challenges while meeting the practical demands of modern biometric recognition systems.

2 Related Work

[1] In their 1996 paper, Brislawn et al. present the FBI's fingerprint image compression standard, developed to enhance the storage and transmission of digitized fingerprint data. The authors emphasize the challenges posed by the high resolution and large size of fingerprint images, which hinder efficient data management. To overcome these issues, they introduce a specialized compression technique tailored for fingerprint images. This method significantly reduces data size while maintaining essential ridge and minutiae details crucial for accurate identification. By balancing compression efficiency with image quality retention, the standard ensures reliable fingerprint recognition, making it a cornerstone in biometric and forensic applications.

[2] This paper presents an innovative image coding technique that combines wavelet transforms, vector quantization, and zero-tree encoding to enhance image compression efficiency. The authors examine how wavelet transforms decompose images hierarchically, preserving both high- and low-frequency details. Vector quantization is utilized to classify similar image data into codebooks, effectively reducing redundancy and improving compression rates. Furthermore, the zero-tree algorithm leverages spatial relationships among wavelet coefficients to detect and discard statistically insignificant values, further optimizing compression while maintaining critical image features. This integrated approach achieves high compression efficiency, making it a valuable technique for storage and transmission of digital images.

[3] In their 2009 book *Handbook of Fingerprint Recognition*, Maltoni et al. provide an in-depth exploration of fingerprint recognition techniques, bridging theoretical principles with practical applications in biometric identification. The book systematically covers key stages of fingerprint recognition, including image acquisition, feature extraction, matching, and verification. It examines fundamental methods such as minutiae-based and ridge-based matching, highlighting the role of image enhancement in boosting recognition accuracy. Furthermore, the authors discuss challenges such as image quality degradation, noise interference, and inter-individual fingerprint variability, offering

strategies to address these issues in real-world biometric systems for enhanced reliability and security.

[4] In their 2005 study, Sudhakar et al. introduce an advanced fingerprint compression technique that integrates the contourlet transform with a modified Set Partitioning in Hierarchical Trees (SPIHT) algorithm. The authors provide a comprehensive analysis of the limitations of traditional fingerprint compression methods, which often struggle to capture the complex multi-scale and directional features present in fingerprint images. To address these limitations, they propose the contourlet transform as a more effective alternative, enabling the efficient representation of fingerprint images at multiple scales and directions. The use of this transform enhances compression performance when compared to conventional wavelet-based methods. In addition, the modified SPIHT algorithm optimizes compression efficiency by adaptively encoding the transformed image, ensuring that critical fingerprint details are preserved. The proposed technique demonstrates a favorable balance between compression ratio and image quality, making it particularly well-suited for large-scale biometric systems.

[5] In their 2014 paper, Shao et al. propose a fingerprint compression technique leveraging sparse representation to address the challenge of efficiently compressing fingerprint images while retaining critical identification details. The authors introduce sparse coding, a method that represents fingerprint images as a linear combination of a limited number of basic functions, enabling more compact storage. This technique effectively reduces data size without compromising the essential features required for accurate fingerprint recognition. The paper demonstrates that sparse representation achieves higher compression ratios than traditional methods, while maintaining the quality of fingerprint images. The proposed approach offers a promising solution for large-scale biometric systems, where efficient storage and transmission of fingerprint data are critical.

[6] In their 2009 *Handbook of Fingerprint Recognition*, Jain, Maltoni, Miao, and Prabhakar offer an extensive examination of fingerprint recognition techniques, spanning foundational concepts to advanced methods utilized in contemporary systems. The book systematically covers the stages of fingerprint recognition, including image acquisition, feature extraction,

matching algorithms, and verification processes. The authors also address key challenges, such as variability in fingerprint quality, distortion, and the demands of real-time processing for large-scale biometric applications. They delve into minutiae-based and ridge-based matching techniques, emphasizing the critical role of accurate feature extraction in achieving high recognition accuracy. This comprehensive resource serves as a vital reference for both academic researchers and practitioners in the field of biometric systems.

[7] Khaldi and Benzaoui (2021) propose an innovative framework for grayscale ear image recognition that utilizes Generative Adversarial Networks (GANs) to address challenges inherent in real-world biometric applications, such as variations in lighting, pose, and occlusions. Their method leverages the power of GANs to generate high-quality synthetic samples, which enhances the diversity of training data and improves the model's robustness. In contrast to traditional feature extraction and classification techniques, deep learning approaches—particularly GANs—demonstrate superior performance in capturing intra-class variations and generating realistic synthetic data, which is crucial in ear recognition tasks. The framework is evaluated using publicly available ear image datasets, and the results show that it outperforms state-of-the-art methods. This study contributes to the growing body of research on biometric recognition, particularly by highlighting the potential of GANs in mitigating data limitations and improving recognition accuracy. It provides valuable insights for future research in biometric identification under unconstrained conditions.

[8] In their 2007 paper, Esakkirajan et al. introduce an advanced fingerprint compression technique that combines the contourlet transform with multistage vector quantization. The authors address the limitations of traditional compression methods and propose the contourlet transform as a more efficient tool for capturing the directional and multi-scale features inherent in fingerprint images. This approach enhances compression efficiency while preserving the critical details necessary for accurate fingerprint recognition. Additionally, the use of multistage vector quantization further reduces data size without compromising image quality. Experimental results show that this technique outperforms conventional methods, providing superior compression ratios and improved reconstruction quality. This innovative approach offers significant advantages for applications

requiring efficient fingerprint data storage and transmission.

[9] Turk et al. (2023) introduce a novel palm print recognition system that utilizes deep learning-based Region of Interest (ROI) features in combination with a hybrid approach. Their method extracts discriminative features from palm print images using deep learning, significantly improving recognition accuracy, especially under challenging conditions such as lighting variations and distortions. Traditional palm print recognition techniques, which rely on handcrafted features and classical machine learning methods, often struggle with these real-world variations. By integrating deep feature extraction with a hybrid classification strategy, the proposed system enhances both robustness and efficiency in palm print recognition. The method is evaluated on benchmark palm print datasets, showing superior performance compared to conventional approaches. This work contributes to the advancement of biometric systems by offering a more accurate and adaptable solution for palm print recognition.

[10] In their 2010 paper, Zhou, Guo, and Wu propose a fingerprint image compression algorithm utilizing matrix optimization techniques to address the challenges of efficient compression while maintaining high recognition accuracy. The approach reduces data redundancy by optimizing the structure of fingerprint image data, thus enhancing compression performance. This method preserves essential fingerprint features crucial for identification, resulting in improved compression ratios and reconstruction quality compared to traditional methods. The paper demonstrates that matrix optimization facilitates efficient storage and transmission of fingerprint images without significant loss of detail. The authors emphasize the suitability of this approach for large-scale biometric systems, providing an effective solution for managing fingerprint databases and improving performance in fingerprint recognition and forensic applications.

3 Methodology

3.1 Architecture Diagram

To enhance the lexicon and improve patch representation, the mean value of each patch is first calculated and subtracted from the patch. This step normalizes the data, ensuring that the representation

focuses on the variations within the patch. The sparse representation of each patch is then determined by solving the l_0/l_1 minimization problem, aiming to identify the most significant coefficients that best represent the patch. Coefficients with absolute values below a predefined threshold are discarded as negligible. For each patch, four key parameters are recorded: the mean value, the number of atoms used, the coefficient values, and their respective locations within the patch.

To further optimize performance, Orthogonal Matching Pursuit (OMP) is recommended over traditional Matching Pursuit (MP) for dictionary construction. Unlike MP, which may repeatedly select the same atom, OMP ensures that once an atom is selected, it is excluded from subsequent selections. This feature reduces algorithmic complexity and accelerates the overall process. Given the relatively simple structure of fingerprint images—dominated by ridges and valleys—the local regions exhibit substantial uniformity. As a result, leveraging OMP for dictionary construction and sparse representation can improve both compression efficiency and reconstruction quality, making it particularly well-suited for fingerprint image compression tasks. This approach facilitates better performance in terms of compression ratio and computational efficiency, providing a robust method for handling large-scale biometric data.

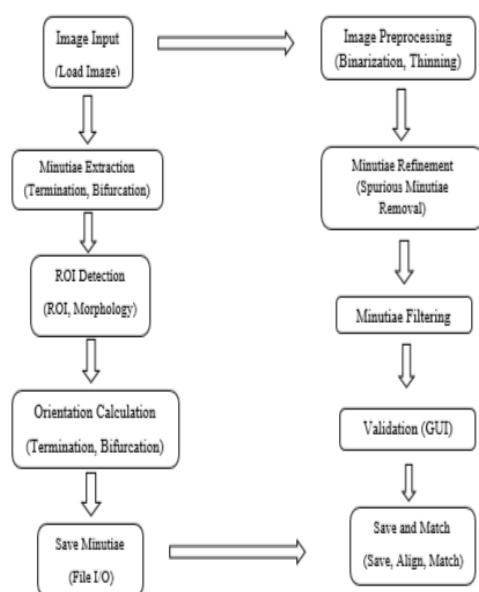


Fig 1: Architectural diagram

3.2 Patch Processing & Mean Removal

In fingerprint compression using sparse representation, the initial step involves patch processing and mean removal. The fingerprint image is divided into small, overlapping or non-overlapping patches to efficiently capture local structures and details. For each patch, the mean value is calculated and subtracted, normalizing the data. This normalization step ensures that intensity variations, which are not relevant to the underlying fingerprint patterns, do not affect the sparse representation process. By centering the data around zero, the dictionary learning process is optimized, improving the accuracy and effectiveness of sparse coding. This approach is crucial for feature extraction, as it removes intensity biases and highlights the essential fingerprint features. Given that fingerprint patterns consist mainly of ridges and valleys, the normalization step aids in preserving these patterns, enhancing the overall compression and reconstruction quality. Thus, mean removal plays a pivotal role in improving the performance of fingerprint image compression, particularly when using sparse representation techniques.

3.3 Data Storage for Each Patch

In fingerprint compression using sparse representation, efficient data storage for each patch is essential to ensure accurate reconstruction while minimizing memory usage. Each patch requires the storage of four key components: the mean value, the number of dictionary atoms used, the sparse coefficients, and their respective locations. The mean value is critical for restoring the original intensity levels during decompression. The number of atoms reflects the sparsity of the representation, striking a balance between compression and fidelity. Sparse coefficients represent the patch in a lower-dimensional space, capturing essential features with reduced data. The locations of these coefficients are recorded to ensure precise reconstruction. This efficient storage approach not only minimizes memory usage but also preserves the critical fingerprint details necessary for maintaining high recognition accuracy, making it a fundamental part of effective fingerprint compression techniques.

3.4 Dictionary Learning & Representation

Dictionary learning and sparse representation are key to effective fingerprint compression. A dictionary is trained on fingerprint

patches to capture essential structural patterns, with each patch represented as a sparse linear combination of dictionary atoms. Orthogonal Matching Pursuit (OMP) is employed instead of Matching Pursuit (MP) to ensure efficient selection of dictionary atoms, minimizing redundancy and enhancing computational efficiency. Given the ridge-and-valley structure of fingerprint images, a well-designed dictionary optimizes compression while retaining critical features necessary for accurate recognition. This approach significantly reduces storage requirements without compromising reconstruction quality, making it well-suited for large-scale fingerprint recognition systems where both storage and accuracy are crucial.

3.5 Compression & Reconstruction

Fingerprint compression using sparse representation involves efficient encoding and decoding of fingerprint patches. Each patch is sparsely represented with a learned dictionary, storing only a few significant coefficients. The compression process captures the mean value, selected dictionary atoms, and sparse coefficients, effectively reducing data redundancy. During reconstruction, the stored coefficients and dictionary atoms are utilized to reverse the sparse representation, reconstructing the original patches. By employing Orthogonal Matching Pursuit (OMP), this method ensures precise reconstruction with minimal data loss. This technique preserves the integrity of the fingerprint while significantly lowering storage and transmission requirements, making it highly suitable for large-scale biometric systems where efficiency and accuracy are essential.

3.6 Optimization for Fingerprint Structure

Optimization in sparse representation-based fingerprint compression focuses on improving accuracy while preserving key ridge and valley details. Due to the simpler structure of fingerprint images compared to natural images, this approach enhances data representation efficiency. By employing Orthogonal Matching Pursuit (OMP) instead of Matching Pursuit (MP), the method ensures the selection of distinct dictionary atoms, reducing redundancy and computational complexity. Structural constraints are also applied to maintain ridge continuity, preventing distortion during reconstruction. The optimization process refines the dictionary learning phase, aligning extracted features with the unique characteristics of

fingerprints. This results in a compressed yet precise representation, enhancing both storage and transmission efficiency, making it ideal for large-scale biometric systems.

4 Proposed Work

Traditional fingerprint compression algorithms often suffer from a significant limitation: their inability to adaptively learn and optimize the dictionary for different fingerprint patterns, leading to suboptimal compression performance. To overcome this, a novel approach based on sparse representation is proposed in this paper. This method dynamically updates the dictionary during the compression process to improve efficiency. Initially, a base matrix is constructed, where each column represents a distinct fingerprint feature, forming a dictionary of atoms. The fingerprint image is then divided into small, non-overlapping patches, each of which is sparsely represented as a linear combination of the dictionary atoms.

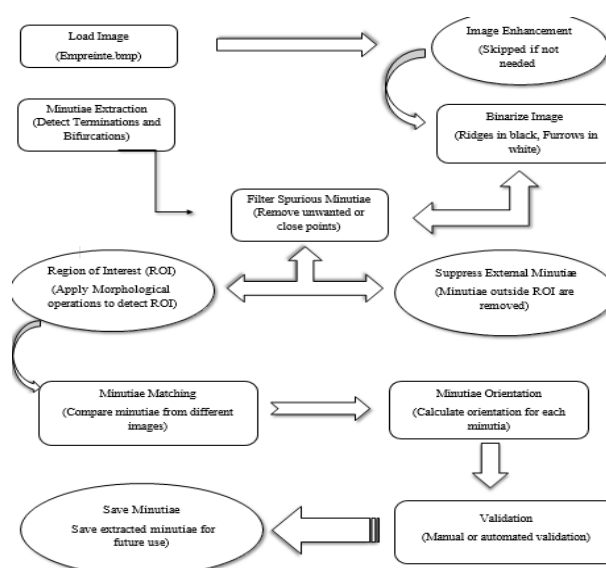


Fig 2: Proposed Work

5 Experimental and Results

In this fingerprint analysis workflow, key stages for minutiae extraction and matching are systematically outlined. Initially, the fingerprint image undergoes pre-processing, which includes binarization, thinning, and minutiae detection. Spurious minutiae are then removed based on proximity criteria to ensure accuracy. A region of interest (ROI) is defined using morphological

operations, and minutiae outside of this region are suppressed to focus on the relevant features. The orientation for each minutia is computed using a predefined table, ensuring precise matching. After thorough validation, the minutiae are saved in a text file for further processing. The ultimate goal is to develop an automated fingerprint matching system, incorporating a graphical user interface (GUI) for interactive validation and matching.

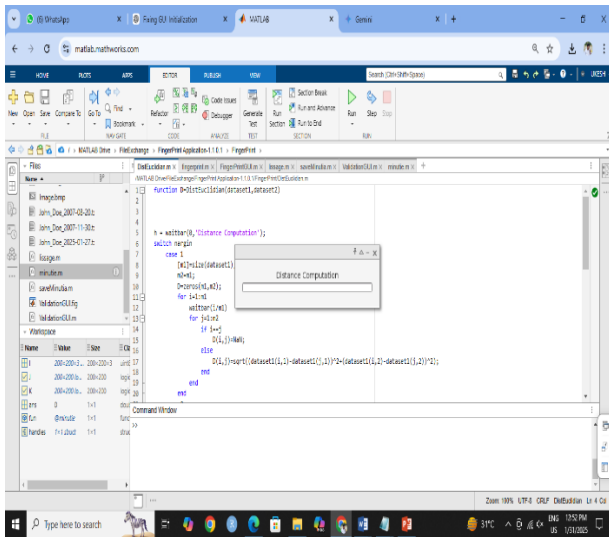


Fig 3: Distance computation

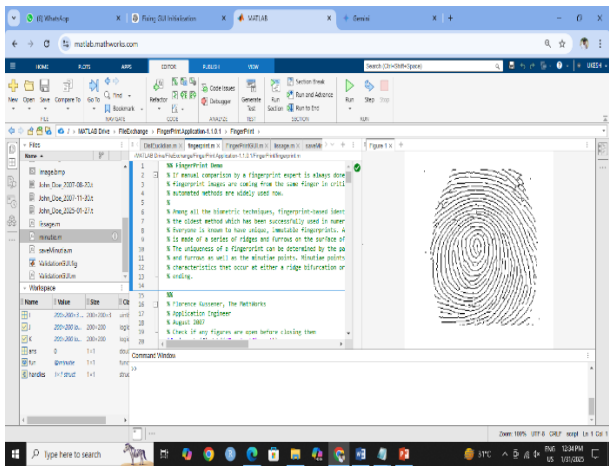


Fig 4: fingerprint

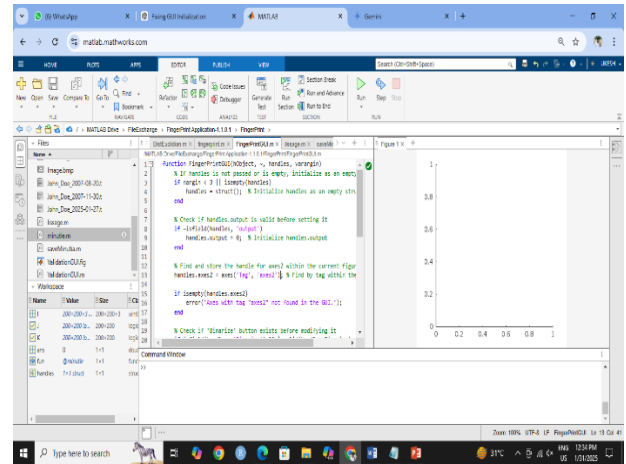


Fig 5: fingerprint GUI

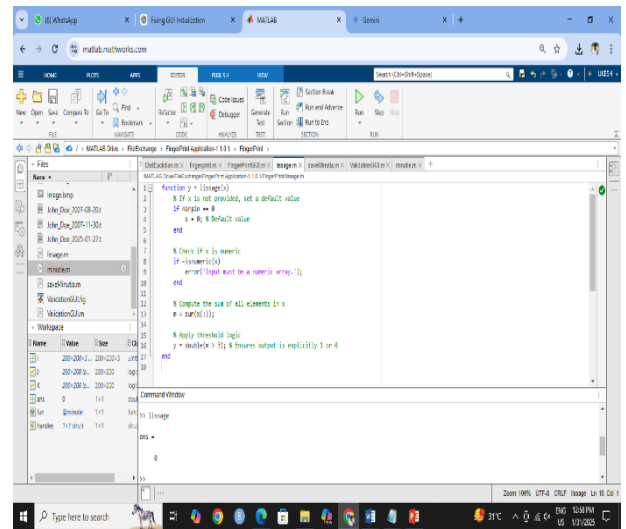


Fig 6: lissage

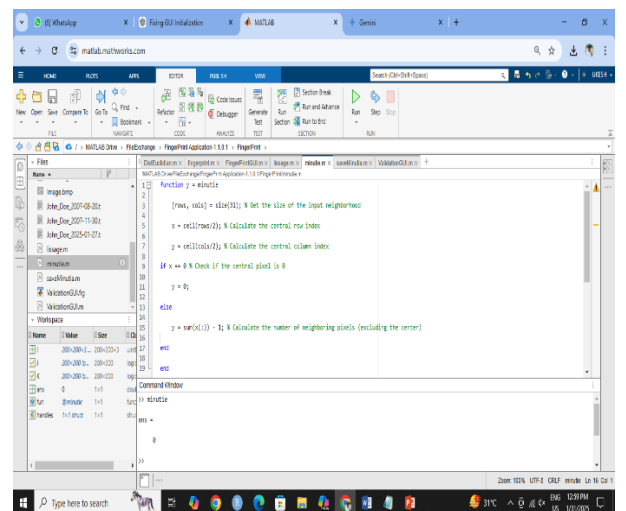


Fig 7: minutiae

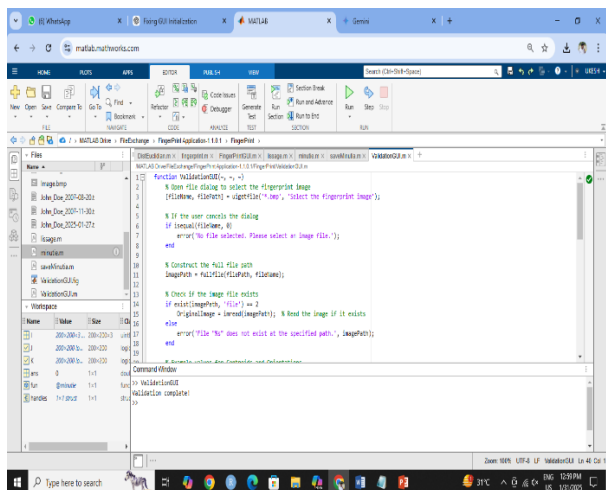


Fig 8: ValidationGUI

6 FUTURE WORK

Future research in fingerprint compression using sparse representation offers significant opportunities to further improve both efficiency and robustness. A key area for enhancement lies in improving compression efficiency, where more advanced dictionary learning algorithms and deep learning methods, such as auto encoders, can be utilized to generate more compact representations while preserving high image quality. Additionally, adapting compression techniques to account for sensor variability is essential. Developing adaptive models capable of optimizing compression based on sensor resolution and image quality will ensure broader applicability across a variety of devices. Another important direction is increasing robustness against noise, as fingerprint images are often subject to distortions. Improving the algorithm's resilience to such noise will enhance its performance in real-world conditions. Finally, advancements in real-time processing through hardware acceleration and parallel computing are crucial for making fingerprint compression feasible for large-scale biometric systems, where both speed and efficiency are critical. These directions will pave the way for more effective, scalable, and versatile fingerprint compression solutions.

7 CONCLUSION

This paper presents a comprehensive review and comparative analysis of various compression techniques specifically designed for fingerprint images, with a particular focus on achieving high compression ratios. A novel compression algorithm

based on sparse approximation is introduced, and its performance is evaluated using two distinct sets of fingerprint images. Experimental results demonstrate that the sparse algorithm outperforms traditional compression techniques such as JPEG, JPEG 2000, WSQ, and K-SVD, particularly at higher compression ratios, while maintaining most of the critical fingerprint details during compression and reconstruction. However, the sparse algorithm introduces higher computational complexities due to its block-by-block processing mechanism, necessitating optimization of the code for different compression techniques to reduce this complexity.

The proposed method combines SPIHT and K-SVD compression techniques, focusing on sparse representation, which is highly effective at high compression ratios. One of the major challenges in fingerprint compression is the preservation of minutiae, which are essential for accurate identification. Experimental results show that the proposed method successfully retains minutiae during compression and reconstruction. The preprocessing phase benefits from the application of FFT, which simplifies the sparse representation approach. Furthermore, increasing the size of the training set improves compression performance.

To enhance the quality of compressed fingerprint images and improve matching accuracy, a Wiener2 filter is applied during decompression. This filter effectively reduces noise and preserves more minutiae, although it does not restore broken ridges. The method could be further refined to better preserve ridge structures. Future research may focus on latent fingerprint compression, particularly for crime scene applications.

Additionally, this study introduces a novel joint sparsity-based feature-level fusion algorithm for multimodal biometric feature extraction. The algorithm is robust as it accounts for noise and occlusion, with features being extracted independently and fused using the sparsity-based fusion method to create a fused template. Various quality metrics such as PSNR, NAE, and NCC are employed to assess image quality. Sobel edge detection is utilized for feature extraction, followed by sparse representation for fusion. The fused template can be used for watermarking and person identification applications. The CASIA database serves as the basis for biometric image testing, and future work will focus on watermarking the fused template.

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