Enhanced Fingerprint Recognition using a Hybrid Technique of Morphological Minutiae Extraction and GLCM Features from Canny Filtering

التعرف المحسن على البصمات بتقنية تجمع بين الاستخلاص المورفولوجي للبصمات وصفات مصفوفة التوافق الرمادي من تصفية كاني

Abdulgader Ab Sinusi
Department of Computer Sciences,Higher Institute of Sciences and Technology, Soq Alkamis Msehel –Libya

عبدالقادر ابوبكر السنوسي
قسم علوم الحاسوب - المعهد العالي للعلوم والتقنية - سوق الخميس مسحل - ليبيا

saih80@yahoo.com

Noureddon H. Beleid
Department of Computer Sciences,Higher Institute of Sciences and Technology - Soq Alkamis Msehel - Libya

نورالدين الهاشمي بلعيد
قسم علوم الحاسوب - المعهد العالي للعلوم والتقنية - سوق الخميس مسحل - ليبيا

nooreb@yahoo.com

Mohamed Maatouk Koum
Mobile Computing Department
Faculty of Information Technology
Tripoli University - Libya

محمد معتوق كوم
قسم الحوسبة المتنقلة كلية تقنية المعلومات جامعة طرابلس - ليبيا

M.koum@uot.edu.ly

Abstract

This review paper presents a comprehensive analysis of an enhanced fingerprint recognition system that integrates Morphological Minutiae Extraction with Gray-Level Co-occurrence Matrix (GLCM) features derived from Canny-filtered images. Biometric recognition, particularly fingerprint-based systems, offers a robust and secure alternative to traditional identification methods due to its reliance on unique and stable biological traits. Despite its widespread use, traditional fingerprint recognition faces challenges such as low-quality images, false acceptance/rejection rates, and spoofing. The aim of this study is to propose a hybrid methodology that addresses these limitations by leveraging Canny filtering for synergistic image enhancement, enabling precise morphological extraction of minutiae (ridge endings and bifurcations) and robust computation of GLCM texture features (contrast, correlation, energy, homogeneity). Future research directions include optimizing hybrid approaches, adaptive parameter tuning, and exploring advanced machine learning techniques to further improve performance and efficiency..

Keywords: Fingerprint Recognition, Hybrid Biometrics, Morphological Operations, Minutiae Extraction, GLCM, Canny Filtering, Feature Fusion, Texture Analysis, Biometric Security.

الملخص

تقدم هذه الورقة البحثية تحليلًا شاملاً لنظام معزز للتعرف على بصمات الأصابع يدمج استخراج المعالم الشكلية مع ميزات مصفوفة التكرار لمستويات الرمادي المشتقة من الصور التي تمت معالجتها بواسطة مرشح كاني. تعالج المنهجية الهجينة المقترحة هذه القيود من خـــلال الاستفادة من تصفية مرشح كاني لتعزيز الصور بشكل متكامـل، مما يتيح استخراجًا دقيقًا للشكل الدقيق (نهايات الحواف والتفرعات) وحسابًا قويًا لميزات مصفوفة التكرار للمستوى الرمادي (التباين، الارتباط، الطاقة، التجانس) .

الكلمات المفتاحية :التعرف على بصمات الأصابع، البيومترية الهجينة، العمليات المورفولوجية، استخراج الدقائق، مصفوفة التكرار لمستويات الرمادي، تصفية كاني، دمج الميزات، تحليل النسيج، أمان البيومترية.

1. Introduction

1.1. Overview of Biometric Recognition and its Importance

Biometric recognition has become an essential component of the contemporary digital landscape, offering a robust and secure alternative to traditional identification and verification methods. Unlike systems based on knowledge, such as passwords, or possession, like smart cards, biometrics relies on the inherent characteristics of an individual, focusing on "who someone is" rather than "what someone knows" or "what someone has".This fundamental reliance on intrinsic biological traits makes biometric systems significantly more resilient against fraudulent activities, including forging or spoofing (Ghafourian et al, 2025).

The inherent advantages of biometric recognition, which include a high level of security, an enhanced user experience, and rapid recognition processes, have spurred its widespread adoption across diverse applications. These range from sophisticated authentication systems to critical border control operations. In modern computer science, biometrics encompasses the automated utilization of both physical traits, such as hand geometry, fingerprints, face, and iris, and behavioural characteristics, like signatures or keystrokes, for personal identification and security pattern recognition. The fundamental shift towards biometric recognition is directly attributable to its reliance on inherence, which translates into superior robustness against traditional fraud(Keepnet, (2025)

1.2. Significance of Fingerprint Recognition

Among the various biometric modalities, fingerprint recognition stands out as one of the most established and widely utilized techniques for personal identification. Its enduring popularity, spanning over a century, is attributed to its unique combination of feasibility, distinctiveness, permanence, accuracy, reliability, and broad acceptability (Raja,2010).

The sustained and widespread adoption of fingerprint recognition for over a century underscores its proven practical effectiveness and established societal trust. This historical success positions it as a foundational benchmark within the biometric field, against which the performance and viability of newer or enhanced recognition methodologies are frequently evaluated.

Fingerprints are unique patterns formed by ridges and valleys on the human fingertip. These patterns are characterized by specific local features known as minutiae points, primarily ridge endings, where a ridge terminates, and ridge bifurcations, where a ridge splits into two or more branches (Innovatrics, 2025).The technology leverages these unique patterns by capturing images, extracting specific features, creating digital templates, and employing pattern-matching algorithms for secure identity authentication and verification across a multitude of applications, including device access, building entry, and sensitive information control (Raja,2010).

1.3. Challenges in Traditional Fingerprint Recognition

Despite its pervasive use and inherent strengths, traditional fingerprint recognition systems face significant challenges that can impede their accuracy, reliability, and widespread deployment.

One such challenge is Failure to Enrol (FTE), which occurs when a biometric template cannot be successfully created for an individual. This can be due to low-quality reference information, perhaps from sensor limitations or poor environmental conditions like lighting, or physical/medical conditions affecting the finger. Cultural or religious sensitivities can also limit an individual's participation (OVIC, 2025).Ensuring effective enrolment rates is crucial for the successful operation of any biometric verification or authentication system.

Biometric systems are also prone to two fundamental types of errors: False Acceptance Rate (FAR) and False Rejection Rate (FRR). A "false positive," or FAR, occurs when the system incorrectly matches an input to a non-matching template, granting unauthorized access. Conversely, a "false negative," or FRR, happens when the system fails to detect a match between an input and a legitimate matching template, denying access to an authorized user.[2] These errors can stem from inherent biometric similarities, such as those found in identical twins, variations in user interaction with the sensor, physiological changes due to aging or injury, or biases in the system's training data (OVIC, 2025). The matching process is inherently probabilistic, with margins for error influenced by a range of factors, including the characteristics of the sample data used for training or the lighting and posture of the individual during acquisition (OVIC, 2025).

Spoofing attacks represent another vulnerability. While biometric identification offers advantages for identity management, it is not a foolproof solution against fraud. Systems can be compromised by "spoofing," where fake artifacts, such as replica fingers or 3D-printed molds, are used to deceive sensors (Geegsforgeegs(2023). Although techniques like liveness detection aim to counter this threat by distinguishing between live human samples and fake representations, the risk of sophisticated adversarial attacks persists (Geegsforgeegs(2023).

A pervasive challenge is the acquisition of low-quality fingerprint images, often resulting from factors like dry or wet fingers, scars, dirt, or inconsistent pressure during capture. Such degraded images make the reliable extraction of minutiae difficult, frequently leading to the detection of "false minutiae" (spurious features) or the omission of genuine ones (Raja,2010). This issue is particularly pronounced with partial fingerprints, where the limited contact area further restricts the number of available feature points (Mohamed Abdul Cader et al., 2023). The pervasive issue of low-quality images is not an isolated problem but a critical root cause that exacerbates multiple other challenges within traditional fingerprint recognition. It directly contributes to failure to enrol, increases false acceptance and rejection rates, and significantly hinders reliable minutiae extraction by introducing spurious features. This highlights that improvements in the initial image acquisition and preprocessing stages are foundational to mitigating a cascade of downstream performance issues.

Furthermore, computational and implementation costs can be a barrier. Deploying biometric security systems often necessitates significant investment in specialized hardware, software, and system integration (Geegsforgeegs, 2023). Certain algorithms, particularly global minutiae matching, can be computationally intensive, impacting processing speed and scalability (Vibert et al., 2023). Finally, non-linear distortion poses a problem. Fingerprints, being three-dimensional structures, are captured by two-dimensional sensors. The inherent plasticity of human skin can introduce non-linear distortions between successive acquisitions of the same finger, complicating the matching process (Vibert et al., 2023).

1.4. Introduction to Hybrid Approaches in Biometrics

To address the inherent limitations and vulnerabilities of unimodal biometric systems, researchers have increasingly turned to hybrid approaches. These systems combine information from two or more types of biometric systems or diverse information sources. The primary objectives of hybrid systems are to enhance recognition accuracy, bolster security assurance, and effectively overcome issues such as noise, poor data quality, and non-universality that can plague single-trait systems (Byahatti, & Shettar, 2020). The adoption of hybrid biometric systems is a strategic response to the inherent probabilistic nature and vulnerabilities of unimodal systems. By combining diverse and complementary feature sets, hybrid approaches aim to reduce the margins for error in probabilistic calculations and simultaneously optimize the often-conflicting goals of security (low FAR) and usability (low FRR), thereby providing a more robust and reliable authentication decision.

The fusion of biometric information can occur at various stages within the recognition pipeline, broadly categorized into fusion before matching and fusion after matching. Specific levels of fusion include sensor level, feature level, score level, rank level, and decision level(Byahatti, & Shettar, 2020). It is generally posited that fusion applied as early as possible in the recognition process, such as at the feature level, tends to be more effective due to the richer information available (Byahatti, & Shettar, 2020).

In the context of fingerprint recognition, hybrid matchers are recognized as powerful tools, particularly for high-security applications where the reliability of a single fingerprint characteristic might be insufficient (Ross, Jain & Reisman,2003).These systems commonly integrate a minutia point matcher with other complementary fingerprint features, such as grayscale image correlation or ridge structure correlation Ross, Jain & Reisman,2003).

1.5. Purpose and Scope of the Review Paper

This review paper aims to provide a comprehensive analysis of an enhanced fingerprint recognition system that employs a specific hybrid technique. This technique integrates "Morphological Minutiae Extraction" and "GLCM Features from Canny Filtering." The paper will systematically detail the fundamental principles and methodologies of each component, elucidate their synergistic integration, and critically discuss the resulting advantages and persistent challenges. Furthermore, it will explore promising future research directions within this specialized domain of hybrid fingerprint recognition.

2. Related Literature

2.1 Methodology of the Hybrid Technique

The proposed enhanced fingerprint recognition system leverages a hybrid approach that combines structural features (minutiae) extracted using morphological operations with textural features derived from Gray-Level Co-occurrence Matrices (GLCM) applied to Canny-filtered images. This methodology aims to capitalize on the strengths of both feature types to achieve higher accuracy and robustness.

2.2. Fingerprint Image Preprocessing with Canny Filtering

2.2.1. Role of Preprocessing in Fingerprint Recognition

Preprocessing constitutes the foundational initial stage in any robust biometric system. Its primary function is to enhance the quality of the raw input image, effectively mitigating the impact of noise, artifacts, and background interference, while also performing necessary normalizations (Ghafourian et al. 2023). This stage is critically important as it directly influences the accuracy and reliability of all subsequent processes, particularly feature extraction and matching. Effective noise reduction is paramount to prevent the generation of false detections or spurious features in later stages (Winarno, et al.,2021). The overall quality of image processing, and consequently the system's performance, is heavily dependent on the efficacy of the segmentation process, which isolates the fingerprint foreground from the background.[22] Preprocessing, through its functions of noise reduction and image enhancement, acts as a critical integrity gate for the entire fingerprint recognition pipeline. Its effectiveness directly dictates the upper bound of reliability for all subsequent feature extraction and matching stages. A robust preprocessing step can significantly mitigate errors originating from poor image acquisition conditions, thereby fundamentally improving overall system accuracy and reducing error rates (FAR/FRR) in downstream operations. If preprocessing fails to adequately remove noise or enhance clarity, these imperfections will propagate through the system, leading to inaccurate feature extraction, such as spurious minutiae, and unreliable texture analysis, which in turn degrades the performance of the matching algorithm. Therefore, preprocessing is not merely a preliminary step but a foundational determinant of the entire system's performance ceiling.

2.2.2. Detailed Explanation of Canny Edge Detection Algorithm

The Canny edge detection algorithm, introduced by John F. Canny in 1986, is widely acclaimed as an optimal and highly robust multi-stage edge detector capable of identifying a broad spectrum of edges within images (Chouhan, & Shukla, 2011). Its reputation stems from its adherence to three core criteria: achieving a low error rate, ensuring good localization of edges, and providing a single response to each true edge (Pan et al., 2025).

The algorithm systematically processes an image through five distinct steps:

1. Noise Reduction (Smoothing): Initially, a Gaussian filter, a low-pass filter, is applied to the image to smooth out noise. This step is crucial given that all edge detection methods are susceptible to image noise.The selection of the Gaussian kernel size is critical, as a larger kernel reduces noise sensitivity but can slightly increase localization error and potentially lead to missing weak edges (Bu, Lazarou, & Stathaki, 2024).

2. Finding Intensity Gradients: The next step involves computing the intensity gradients of the smoothed image to determine the edge strength (magnitude) and orientation (angle) (Bu, Lazarou, & Stathaki, 2024. This is typically achieved by convolving the image

with Sobel kernels in both horizontal and vertical directions (Pan et al.,2025)

3. Non-Maximum Suppression: To ensure that only local maxima in the gradient magnitude are marked as edges, a non-maximum suppression step is performed. This process effectively thins the detected edges to a single-pixel width, thereby removing spurious responses and ensuring precise edge localization(Bu, Lazarou, & Stathaki, 2024).
4. Double Thresholding: Potential edges are identified using two global threshold values: a high threshold and a low threshold. Pixels with gradient magnitudes above the high threshold are classified as strong edges. Pixels with magnitudes between the high and low thresholds are considered weak edges, while those below the low threshold are suppressed as non-edges (Bu, Lazarou, & Stathaki, 2024).
5. Edge Tracking by Hysteresis: The final stage involves hysteresis thresholding, which connects weak edges to strong ones. Weak edges are preserved only if they are connected to a strong edge neighbor; otherwise, they are suppressed as potential noise or color variations (Bu, Lazarou, & Stathaki, 2024). This ensures that only meaningful edges are retained while isolated noise is eliminated.

The adjustable parameters within the Canny algorithm, notably the size of the Gaussian filter and the double thresholds, introduce a critical trade-off that significantly impacts its performance on fingerprint images (Bu, Lazarou, & Stathaki, 2024). A larger Gaussian filter, while effective at noise reduction, can lead to increased localization error and a higher likelihood of missing subtle, weak edges. Similarly, improperly set thresholds can either miss important information (if too high) or falsely identify noise as edges (if too low) (Bu, Lazarou, & Stathaki, 2024. This implies that achieving optimal Canny performance for fingerprint images necessitates careful, context-specific tuning to strike a balance between noise suppression, edge preservation, and computational efficiency. Sub-optimal Canny output will inevitably degrade the quality of both morphological minutiae extraction and GLCM feature computation in the subsequent stages of the hybrid system.

2.2.3. Application of Canny Filtering for Fingerprint Enhancement

In the context of fingerprint recognition, Canny filtering serves as a pivotal enhancement technique, primarily by sharpening the appearance of ridges within the fingerprint image (MATLAB Help Center, 2025). Its robust edge detection capabilities make it an ideal core technique for extracting precise edge information, which is fundamental for subsequent feature extraction processes (Bhat, & Szczuko, 2025). Studies have shown that Canny edge detection, when used as a preprocessing step, can influence computational aspects such as model memory footprints and prediction latencies, especially when combined with other filtering techniques.The algorithm's ability to operate across multiple colour channels, such as RGB, allows for comprehensive edge information extraction, even from complex image datasets Bhat, & Szczuko, 2025).Canny's robust edge detection capability offers a dual benefit for the proposed hybrid system. It effectively enhances the structural integrity of ridge lines, which is crucial for accurate morphological minutiae extraction, and simultaneously sharpens the texture patterns, making GLCM features more discriminative. This positions Canny as a synergistic preprocessing step, providing an optimally prepared image that maximizes the quality of both primary feature types in the hybrid approach. By producing clearer, well-defined ridge edges, Canny directly improves the precision with which morphological operations can identify minutiae points. Concurrently, these sharpened edges contribute to more distinct and measurable texture patterns, thereby improving the discriminative power of GLCM features.

2.3. Morphological Minutiae Extraction

2.3.1. Fundamentals of Minutiae (Ridge Endings and Bifurcations)

Minutiae are the most fundamental and widely recognized distinctive local features within a fingerprint pattern. They are typically categorized into two primary types: ridge endings, which are points where a ridge abruptly terminates, and ridge bifurcations, where a single ridge splits into two or more branches(Innovatrics, 2025). These features are paramount in both manual and automated fingerprint recognition due to their concise nature, highly discriminative cues, and remarkable stability across different impressions of the same finger. The inherently random distribution of minutiae across a fingerprint provides sufficient discriminative information for robust identification, enabling effective recognition even with traditional point-matching algorithms (Jain, Ross, & Prabhakar, 2001). A high-quality fingerprint typically contains a substantial number of minutiae, ranging from 25 to 80, depending on factors such as sensor resolution and finger placement (Raja, 2010). While minutiae possess intrinsic properties of high discriminability and stability, their practical extraction is severely hampered by real-world image quality issues. This gap between their theoretical discriminative power and the difficulty in reliably extracting them from imperfect data is a primary impetus for employing sophisticated image processing techniques like morphological operations and for integrating minutiae with other complementary features in a hybrid system (Raja, 2010).

2.3.2. Role of Morphological Operations in Feature Extraction

Morphological operations constitute a powerful set of image processing techniques that analyze images based on shapes and structures, rather than merely altering their visual appearance. They are instrumental in identifying objects, boundaries, and internal structures within an image, playing a crucial role in applications like machine vision and automatic object detection. These operations are predominantly applied to binary images, where pixel values are typically 0 or 1. (Suresh & Shunmuganathan, 2012).

The most fundamental morphological operations are erosion and dilation. Erosion removes pixels from object boundaries, effectively shrinking or thinning objects and making lines appear finer. Dilation, conversely, adds pixels to boundaries, growing or thickening objects and filling small holes. These two operations form the basis for more complex morphological operators (Suresh, & Shunmuganathan, 2012):

- Opening: An erosion followed by a dilation, useful for removing small objects and thin lines while preserving the shape and size of larger objects.
- Closing: A dilation followed by an erosion, effective for filling small holes in an image while preserving larger ones.
- Skeletonization (Thinning): A process that erodes objects down to their centerlines without altering their essential topological structure, such as the presence of holes or branches. This is crucial for reducing ridge widths to a single pixel.
- Pruning: A complementary technique to skeletonization and thinning, used to remove unwanted parasitic components like spikes or spurs that can be misidentified as minutiae.

In fingerprint recognition, morphological operations are vital for transforming the image into connected lines, which greatly facilitates the identification of minutiae points 27 (Batool et al., 2024). They are specifically employed to refine the ridge map by removing artifacts such as spikes, spurs, and dots, thereby ensuring a cleaner and more accurate basis for minutiae detection. 26 (Sebastian et al.,2012). Morphological operations are not merely about extracting features; they are fundamentally about refining the image's structural representation to enable precise and reliable minutiae detection. Thinning ensures single-pixel width ridges, which is a prerequisite for accurate minutiae marking, while operations like pruning and opening are critical for eliminating spurious minutiae that arise from noise or imperfections in the original image. This directly addresses the persistent challenge of false minutiae by improving the quality of the extracted feature set.

2.3.3. Steps for Minutiae Extraction

The process of minutiae extraction, particularly from a thinned ridge map, is a multi-stage pipeline designed to identify and refine the unique characteristics of a fingerprint. It typically involves the following sequential steps:

1. Image Segmentation: The initial step involves separating the relevant fingerprint foreground from the irrelevant background. This is often achieved by dividing the image into blocks, computing the variance within each block, and comparing it against a predefined threshold to identify and isolate the active fingerprint area Raja, 2010).

2. Image Normalization: After segmentation, the grayscale intensities within the fingerprint region are normalized to a constant mean and variance. This step is crucial for mitigating the effects of sensor noise and variations in grayscale values caused by differences in finger pressure during acquisition.

3. Binarization: The normalized grayscale image is then converted into a binary (black-and-white) image, where pixels are assigned values of either 0 or 1. This simplification reduces data complexity and prepares the image for morphological operations (2010).
4. Ridge Thinning (Skeletonization): This is a critical morphological operation that reduces the width of each ridge to a single pixel without altering the fundamental structure of the ridge pattern. Thinning is essential because it simplifies the subsequent minutiae detection by ensuring that ridge endings and bifurcations can be unambiguously identified based on pixel connectivity. The objective is to produce a thinned image that is single-pixel wide, free of discontinuities, and has noise and singular pixels eliminated (2010).
5. Minutiae Marking: Once the ridge map is thinned, minutiae points are identified based on their pixel connectivity. A black pixel with only one black neighbour is classified as a ridge ending, while a black pixel with more than two black neighbours is identified as a ridge bifurcation (Thai, 2011). The precision of this step is highly dependent on the quality of the thinned image.
6. False Minutiae Removal (Post-Processing): The initial minutiae extraction process can often yield spurious minutiae due to noise, scars, or imperfections in the fingerprint image. Morphological pruning algorithms are employed in this post-processing stage to remove these unwanted parasitic components, such as spikes, spurs, and isolated dots, thereby ensuring that only valid minutiae are retained for matching

(Thai, 2011). This step significantly improves the reliability of the extracted feature set.

2.4.4. Detecting Ridge Endings and Bifurcations

The detection of ridge endings and bifurcations relies heavily on the skeletonized (thinned) representation of the fingerprint. In a thinned binary image, where ridges are represented by single-pixel-wide lines, the identification of minutiae becomes a straightforward process of analysing pixel neighbourhoods.

A pixel is identified as a ridge ending if it is a black pixel (representing a ridge) and has only one black neighbour within its 3x3 pixel neighbourhood. This indicates the termination of a ridge line. Conversely, a pixel is classified as a ridge bifurcation if it is a black pixel and has more than two black neighbours within its 3x3 pixel neighbourhood. This signifies a point where a ridge splits into multiple paths (Suresh et al., 2012; Hussian et al., (2025).

The accuracy of this detection is directly contingent on the preceding morphological operations, particularly thinning and pruning. A well-thinned image with effectively removed spurious features ensures that the pixel connectivity analysis accurately reflects true minutiae, rather than noise-induced artifacts. This direct relationship between image preparation and feature fidelity underscores the importance of a robust morphological pipeline in reliable minutiae extraction.

2.5. GLCM Feature Extraction

2.5.1.Principles of Gray-Level Co-occurrence Matrix (GLCM)

The Gray-Level Co-occurrence Matrix (GLCM) is a statistical method widely used for image texture analysis. Unlike other texture filter functions, GLCMs consider the spatial relationships of pixels, providing a more comprehensive characterization of image texture. A GLCM characterizes image texture by counting how often pixels with a certain intensity value occur in a specific spatial relationship to pixels with other intensity values.

The GLCM is essentially a two-dimensional histogram where each element (i, j) represents the frequency with which a pixel with intensity 'i' occurs adjacent to a pixel with intensity 'j'. This co-occurrence is defined by a specified spatial relationship, which includes both a distance ('d') and an orientation angle ('θ'). Common orientation angles used are 0°, 45°, 90°, and 135°, allowing for detailed information about the structure and characteristics of the object being analysed across different directions (Roli et al., 2011). The number of gray levels in the image determines the size of the GLCM, and scaling can be applied to reduce the number of intensity values for computational efficiency. If most entries in a GLCM are concentrated along the diagonal, it indicates a coarse texture with respect to the specified offset.

2.5.2. GLCM Features for Texture Analysis (Contrast, Correlation, Energy, Homogeneity)

From the generated GLCM, several statistical measures can be derived to quantify various textural characteristics of an image. These features provide a rich description of the spatial distribution of gray levels and are crucial for texture-based recognition systems. The most commonly extracted GLCM features include:

- Contrast: This feature measures the local variations in the gray-level co-occurrence matrix. High contrast values indicate a large difference in intensity between a pixel and its neighbour, suggesting sharp edges and a high degree of local variability (Batool et al,.2024).
- Correlation: Correlation quantifies the joint probability of occurrence of specified pixel pairs, essentially measuring the linear dependency of gray levels in the image. High correlation values

suggest a strong linear relationship between pixel intensities, indicating a more uniform or less varied texture (Batool et al,.2024).

- Energy (Angular Second Moment): Energy provides the sum of squared elements in the GLCM, also known as uniformity or the angular second moment. It measures the homogeneity or uniformity of the image texture. A high energy value indicates a very uniform texture, where certain pixel pairs occur frequently (Batool et al,2024).
- Homogeneity: Homogeneity refers to the closeness of the distribution of elements to the GLCM diagonal. It measures the spatial closeness of the distribution of elements in the GLCM to the GLCM diagonal. High homogeneity values suggest that the texture is composed of similar grey levels, indicating a more uniform and less varied texture (Batool et al,.2024)

These second-order texture analysis features are effective in representing image textures in measurable parameters and are widely used in various applications, including object detection and classification.

2.3.3. Application of GLCM in Fingerprint Recognition

In fingerprint recognition, GLCM is applied to extract texture features from the image, often after preprocessing steps like Canny filtering. The Canny filter enhances the appearance of ridges, making the texture patterns more distinct and amenable to GLCM analysis) (Batool et al,.2024).

The process typically involves:

1. Preprocessing: The fingerprint image undergoes preprocessing, including Canny filtering, to enhance ridge clarity and reduce noise (Chouhan, & Shukla, S. (2011).

2. Region-of-Interest (ROI) Determination: A unique reference point, often the core point of the fingerprint, is determined to define a Region-of-Interest (ROI) (Batool et al,.2024).This focuses the texture analysis on the most discriminative part of the fingerprint.
3. GLCM Computation: Four co-occurrence matrices are computed from the ROI using predefined distances and the standard four orientations (0°, 45°, 90°, 135°).
4. Feature Extraction: From these GLCMs, a feature vector is formed by extracting statistical measures such as contrast, correlation, energy, and homogeneity (Batool et al,.2024). This feature vector then characterizes the texture of the fingerprint.

The use of GLCM features in fingerprint recognition offers several advantages. It can significantly reduce memory cost and processing time associated with verification due to its efficient feature extraction (Batool et al,.2024). Furthermore, GLCM-based features are particularly effective for fingerprint matching because fingerprints are composed of regular texture patterns. This approach complements minutiae-based methods by providing robust discriminatory information derived from the overall ridge structure, which is particularly useful in cases of low-quality or partial fingerprints where minutiae extraction might be challenging (Bhat & Szczuko, 2025).

2.5. Fusion Strategy for Hybrid Features

2.5.1. Rationale for Feature-Level Fusion

Hybrid biometric systems are designed to overcome the limitations of unimodal systems by combining information from multiple sources. Fusion can occur at various levels, including sensor, feature, score, rank, and decision levels. It is generally believed that fusion applied as early as possible in the recognition system, such as at the feature level, is more effective because it allows for the integration of richer and more discriminative information before any loss occurs during subsequent processing stages (Alqadi et al., 2020).

Feature-level fusion involves extracting features from multiple sources of information and then integrating them into a joint feature vector. This new, high-dimensional feature vector represents an individual more comprehensively (Alqadi et al., 2020). This approach is particularly advantageous as it can extract the maximum discriminative data from the initial feature sets and remove redundant information, leading to improved recognition accuracy and robustness against challenges like noise and spoofing. For the proposed hybrid fingerprint recognition system, combining morphological minutiae features with GLCM texture features at the feature level is logical. Minutiae provide precise local structural information (points), while GLCM provides global textural context (regions). By fusing these distinct yet complementary representations, the system gains a more holistic and robust understanding of the fingerprint, enhancing its ability to differentiate between genuine and imposter attempts, especially in cases of degraded image quality or partial prints where one feature type alone might be insufficient (Singh & Kant, 2025).

2.5.2. Architecture of the Hybrid System

The architecture of the proposed hybrid fingerprint recognition system integrates the two distinct feature extraction pathways—morphological minutiae and GLCM texture features into a unified framework. This system typically involves the following modules:

1. Image Acquisition: The process begins with capturing the fingerprint image using a specialized scanner.
2. Preprocessing (Canny Filtering): The raw fingerprint image undergoes enhancement and noise reduction. Canny filtering is applied to sharpen ridge details and prepare the image for both

minutiae and GLCM feature extraction. This step is crucial for providing a clean input for subsequent stages.

3. Feature Extraction Streams:
    - Morphological Minutiae Extraction: The pre-processed image is subjected to a series of morphological operations, including segmentation, normalization, binarization, ridge thinning (skeletonization), and minutiae marking (Raja, 2010). A post-processing step then removes false minutiae to yield a refined set of ridge endings and bifurcations (Bhat, & Szczuko, 2025). This results in a minutiae template, often characterized by the (x, y) coordinates, orientation, and type of each minutia.
    - GLCM Feature Extraction: Concurrently, the Canny-filtered image (or a specific Region of Interest from it) is used to compute Gray-Level Co-occurrence Matrices. From these matrices, a set of texture features, such as contrast, correlation, energy, and homogeneity, are extracted, forming a GLCM feature vector (Roli et al., 2011).
4. Feature-Level Fusion: The extracted morphological minutiae feature and GLCM texture features are combined to form a single, comprehensive feature vector. This fusion typically involves concatenating the two distinct feature sets (Byahatti, & Shettar, 2020). This combined vector represents a richer and more discriminative description of the fingerprint than either feature set alone.
5. Matching Module: The fused feature vector from the input fingerprint is then compared against stored templates in a database. Various matching algorithms, such as Euclidean distance or

Support Vector Machines, can be employed to compute a similarity score (Raja, 2010).

6. Decision Module: Based on the similarity score and a predefined threshold, the system makes a decision regarding the identity of the individual, either granting or denying access, or identifying a match from a database (Ghafourian et al., 2023).

This dual-stream architecture, followed by feature-level fusion, allows the system to leverage both fine-grained local structural information and broader regional texture patterns. This comprehensive representation is designed to enhance accuracy and robustness, particularly when dealing with challenging fingerprint images (Pan et al,2025).

2.5.3. Integration of Morphological Minutiae and GLCM Features

The integration of morphological minutiae and GLCM features in this hybrid system is achieved through feature-level fusion, creating a more robust and comprehensive fingerprint representation. Minutiae, as point-wise features, provide precise information about ridge discontinuities (endings and bifurcations), which are highly stable and discriminative (Raja, 2010). However, minutiae-based matching can be vulnerable to poor image quality, non-linear distortion, or insufficient numbers of corresponding points in partial prints, leading to spurious or missed minutiae (Raja, 2010).

GLCM features, on the other hand, capture the statistical properties of the texture patterns across the fingerprint image (Singh & Kant, 2025). These features, such as contrast and homogeneity, describe the spatial arrangement of ridges and valleys, providing a region-based, holistic view of the fingerprint's unique pattern (Roli et al., 2011). GLCM is particularly effective for images with regular texture patterns, which fingerprints inherently possess (Batool et al.,2024)

The synergistic integration begins with Canny filtering, which enhances the ridge structures, making them clearer for both morphological processing and texture analysis .[25] Morphological operations then precisely extract the minutiae points by skeletonizing the ridges and removing noise-induced artifacts.[28] Simultaneously, GLCM features are extracted from the Canny-filtered image, providing a texture-based descriptor (Roli et al., 2011). By concatenating these two distinct feature sets the minutiae coordinate and orientations, and the GLCM statistical values a combined feature vector is created (Byahatti, & Shettar,2020). This combined descriptor is significantly more discriminating than any single descriptor alone. This feature-level fusion ensures that the system benefits from both the precise local details provided by minutiae and the robust global texture information from GLCM, thereby compensating for the weaknesses of each individual approach and leading to enhanced recognition performance, especially for low-quality or partial fingerprint images.

3. Results and Discussions

3.1. Advantages of the Hybrid Technique

The proposed hybrid technique, combining Morphological Minutiae Extraction and GLCM Features from Canny Filtering, offers several significant advantages over traditional unimodal fingerprint recognition methods.

Firstly, the hybrid approach substantially enhances recognition accuracy and robustness. Traditional minutiae-based systems can struggle with low-quality images, partial fingerprints, or non-linear distortions, leading to false minutiae or missed genuine features (Roli et al., 2011). By integrating texture features from GLCM, which provide a more global and holistic description of the ridge patterns, the system gains complementary information that is less sensitive to localized imperfections. This combination allows for a more comprehensive representation of the fingerprint, improving the system's ability to differentiate between genuine and imposter attempts (Singh & Kant, 2025). The system's ability to combine multiple, distinct, and complementary measurements creates a more comprehensive "evidence base," which directly enhances the confidence of the probabilistic matching calculation and leads to a more favourable balance between security (reduced FAR) and usability (reduced FRR).

Secondly, the use of Canny filtering as a preprocessing step provides a dual benefit for feature extraction. Canny's robust edge detection sharpens the appearance of ridges, which is critical for the precise identification of minutiae through morphological operations. Simultaneously, these well-defined edges contribute to more distinct texture patterns, thereby improving the discriminative power of the GLCM features. This synergistic preprocessing ensures that both primary feature types operate on an optimally prepared image, streamlining the overall pipeline and enhancing the quality of the combined feature set.

Thirdly, the feature-level fusion strategy is designed to maximize the discriminative power. By concatenating the minutiae and GLCM feature vectors, the system integrates information at an early stage, preserving richer details that might be lost in later fusion levels like score or decision fusion.[17] This comprehensive feature vector becomes more resilient to variations and noise, as the strengths of one feature type can compensate for the weaknesses of the other. For instance, in cases of severe degradation affecting minutiae clarity, the robust texture information can still provide strong discriminatory cues.

Finally, the hybrid method often demonstrates improved performance with low-quality fingerprint images. This is a critical advantage; as poor image quality is a persistent challenge in real-world applications. The combination of structural and textural features, enhanced by effective preprocessing, allows the system to maintain higher accuracy even when dealing with suboptimal input, a scenario where traditional unimodal methods typically fall short (Bhat & Szczuko, 2025).

3.2. Comparison with Traditional Methods

Traditional fingerprint recognition methods primarily rely on either minutiae-based matching or image-based (correlation-based) techniques. The hybrid approach described offers distinct advantages when compared to these conventional methods.

Minutiae-based methods are widely used due to their reliance on unique and stable local features (ridge endings and bifurcations) (Raja, 2010).They are computationally inexpensive for matching and provide good recognition performance under ideal conditions.[16] However, their performance significantly degrades with low-quality or partial fingerprints, where the accurate extraction of a sufficient number of reliable minutiae becomes challenging, leading to high false acceptance and rejection rates (Raja, 2010).The hybrid technique mitigates this by incorporating GLCM texture features, which provide a robust, region-based description that is less susceptible to localized minutiae extraction errors or missing points. This means that even if minutiae extraction is compromised, the texture features can still contribute significantly to the matching decision, leading to a substantial improvement in overall matching performance.

Image-based (or correlation-based) methods compare fingerprint images directly or their transformed representations. While they can capture global information, they are often sensitive to translation, rotation, and non-linear distortion, requiring complex alignment algorithms (Vibert et al., 2023). They can also be computationally intensive, especially for large databases. The proposed hybrid method, by taking the minutiae-based technique as its backbone, benefits from the alignment capabilities derived from minutiae matching. This allows for the effective use of texture information in detailed matching without being overly sensitive to global transformations. Furthermore, the Canny filtering step sharpens the image, making the texture features extracted by GLCM more distinct and reliable than those from raw or less-processed images, thereby enhancing the discriminative power of the texture component (Byahatti, & Hatture, 2017)

Overall, hybrid systems, by combining the strengths of both minutiae and texture features, have demonstrated superior accuracy and robustness compared to their unimodal counterparts. (Alqadi et al., 2020). They effectively address the limitations of single-trait systems, such as noise, poor data quality, and non-universality, leading to improved recognition accuracy and higher security assurance. Studies have shown quantifiable enhancements in both accuracy and efficiency, with hybrid deep learning models achieving significantly reduced false acceptance and rejection rates compared to traditional methods. The hybrid approach provides a more dependable and resilient solution for real-world applications by leveraging diverse information sources (Alqadi et al., 2020).

3.3. Limitations and Challenges

Despite the significant advantages offered by the hybrid technique, several limitations and challenges persist, necessitating ongoing research and development.

Firstly, the computational complexity associated with combining multiple feature extraction methods can be a concern. While GLCM feature extraction can be efficient, especially with a predefined Region of Interest, the overall processing pipeline, including Canny filtering and morphological operations, adds computational overhead. The complexity of the GLCM algorithm itself is related to the number of operations required to produce an $O(n^2)$ matrix, where 'n' is the number of pixels in the image, meaning computation time increases quadratically with image size (Hussian et al., 2024). This can impact real-time performance, particularly for resource-constrained devices or large-scale applications.[26]

Secondly, the quality of the input image remains a critical factor. While the hybrid approach is more robust to low-quality images than unimodal methods, extreme degradation due to factors like severe dryness, wetness, scars, or inconsistent pressure can still compromise feature extraction accuracy (Raja, 2010). The presence of noise or poor contrast can lead to spurious edges from Canny filtering, which in turn can affect both morphological minutiae extraction and GLCM texture analysis. The effectiveness of the Canny algorithm is highly dependent on the proper tuning of parameters like Gaussian filter size and double thresholds, which can be difficult to generalize across all image qualities.

Thirdly, false minutiae and distortion handling continue to be challenges. While morphological pruning helps remove spurious minutiae, imperfect preprocessing can still lead to their presence, affecting matching accuracy. Non-linear distortion due to skin elasticity between successive acquisitions can also complicate the alignment and matching of both minutiae and texture features.[15] Although hybrid methods aim to be more robust, significant displacement differences or non-uniform finger pressure can still pose hurdles (Bu, Lazarou & Stathaki, 2024).

Finally, scalability and interoperability for large-scale databases and diverse sensor types present ongoing challenges. Different sensors can produce varying image qualities and types of distortions, leading to interoperability issues. While the hybrid approach enhances performance, ensuring consistent accuracy and efficiency across vast and varied datasets, especially in real-time scenarios, requires continuous optimization and standardization efforts. The trade-off between security (low FAR) and usability (low FRR) also persists, requiring careful calibration of system thresholds (Kumar, 2025).

4. Conclusion

This review paper has systematically explored an enhanced fingerprint recognition system leveraging a hybrid technique that integrates Morphological Minutiae Extraction and GLCM Features from Canny Filtering. The analysis underscores that biometric recognition, particularly fingerprint-based systems, offers a robust and inherently secure alternative to traditional identification methods, primarily due to its reliance on unique and stable biological traits. The enduring prevalence of fingerprint recognition over a century attests to its proven effectiveness and societal acceptance, establishing it as a foundational benchmark in biometrics.

However, traditional fingerprint recognition faces persistent challenges, including failure to enrol, false acceptance and rejection rates, spoofing vulnerabilities, and critically, the pervasive issue of low-quality input images. This degradation in image quality is not merely an isolated problem but a fundamental root cause that exacerbates downstream performance issues, directly impacting enrolment, accuracy, and reliable feature extraction.,The proposed hybrid methodology addresses these limitations by strategically combining complementary feature types. Canny filtering serves as a pivotal preprocessing step, synergistically enhancing ridge structures for both morphological minutiae extraction and GLCM texture analysis. This ensures that subsequent feature extraction operates on optimally prepared images. Morphological operations precisely refine the structural representation of the fingerprint, enabling accurate minutiae detection while mitigating spurious features. Concurrently, GLCM features capture comprehensive texture patterns, providing robust regional information. The feature-level fusion of these distinct yet complementary representations creates a more holistic and discriminative fingerprint template.The advantages of this hybrid technique are notable: it significantly enhances recognition accuracy and robustness, particularly when confronted with low-quality or partial fingerprints, a common real-world challenge. By integrating the precise local details of minutiae with the robust global texture information, the system achieves a more comprehensive "evidence base" for matching decisions. This leads to a more favourable balance between security (reduced FAR) and usability (reduced FRR) compared to unimodal systems.Despite these advancements, challenges remain, including computational complexity, the persistent impact of extreme image degradation, and the need for robust handling of non-linear distortions. Future research should focus on optimizing these hybrid approaches, exploring adaptive parameter tuning for preprocessing algorithms, developing more sophisticated fusion strategies that dynamically weigh feature contributions based on image quality, and investigating advanced machine learning techniques to further enhance robustness and computational efficiency across diverse operational environments and sensor types. Continued efforts in these areas will be crucial for the widespread deployment of highly accurate and reliable fingerprint recognition systems.

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