International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

An Effective Feature Extraction Algorithms for Ridge Information, Minutia Information and DWT from Fingerprint Image

[1]Chandrakant P. Divate, [2]Dr. Syed Abulhasan Quadri, [3]Dr. V. Sumathi, [4]Dr. N. Rajalakshmi, [5]Hemant Singh Pokhariya, [6]A. Deepak, [7]Dr. Anurag Shrivastava

Submitted: 29/12/2023 **Revised**: 05/02/2024 **Accepted**: 13/02/2024

Abstract: A fingerprint image is a detailed representation of the unique spatial arrangement of ridges and valleys on the fingertip skin. This intricate pattern serves as a distinctive biometric signature, utilized in various applications such as forensic science, security systems, and access control. The complexity and individuality of each fingerprint make it a reliable and secure method for personal identification and verification. The work has been motivated by studies in anthropometry [11], biometric characteristic [3], and pattern recognition [14] suggesting that it is possible to extract more detailed information from ridge, minutia and DWT information from fingerprints. The detailed studies of feature extractions in classification like gender, age, blood etc. using fingerprint only, is essential for its easiness, economical and less complex model to design as compared to other techniques as the fingerprint size results in small storage space. An automated fingerprint classification system compares the features of a test fingerprint with stored data on ridges and valleys in a database. It involves a detailed analysis of spatial patterns, minutiae points, and unique attributes for precise identification. Utilizing advanced algorithms, the system matches the test fingerprint with stored data, facilitating effective recognition in applications like law enforcement, security, and biometric authentication. The result of a fingerprint image is titled as "matching" if both the produced features of the testing image are matched with features of the fingerprints in database, regardless of the time and method by which each image is collected. In most of the existing fingerprint based gender identification systems, the features used are the fingerprint minutiae, mainly ridge bifurcation, ridge count, ridge ending, ridge thickness, valley thickness, ridge thickness to valley thickness ratio (RTVTR), Discrete wavelength transform . etc. However, the fingerprint based features on ridge or minutiae based are developed so far works necessarily, still there are several other characteristics that can also be extracted on ridge and minutiae and utilize it in the classification process. The paper highly emphases on implementation of different algorithms on new features based on first discrete wavelet transform, second ridge length - i.e minimum maximum and average ridge length, and third minutiae information-Ridge bifurcation count(RBC), Ridge end count (REC), Minutia count (μC), those can be extracted from fingerprint images

Keywords: *Fingerprints, Ridge, Minutiae, DWT, Feature extraction, algorithms.*

1. Introduction

In the contemporary era, the global landscape is swiftly moving towards atomization, signifying a paradigm shift in various sectors. Consequently, there arises a recurrent necessity for the preprocessing of biometric data. In the realm of computerized systems, biometric data manifests in diverse forms such as audio, image, and video, among others. To effectively harness the potential of biometric data, an array of sophisticated techniques in image processing and data mining has emerged to meet the specific requirements of diverse applications. In the intricate realm of biometric data, image processing and data mining techniques have witnessed remarkable advancements, empowering a wide range of applications. These technologies play a pivotal role in extracting meaningful insights and patterns from biometric data, contributing to enhanced accuracy and efficiency in identification processes. As per the unique demands of various applications, these techniques are continuously evolving and adapting. In the contemporary landscape, the significance of classification algorithms in the vital operations of data mining has surged notably. Classification algorithms serve as linchpins in the extraction of valuable information from biometric data sets, enabling the categorization and identification of distinct patterns. Their heightened importance stems from their ability to discern and categorize diverse data points, facilitating accurate and efficient decision-making processes. In summary, the ongoing trend towards atomization in the world has engendered a frequent

[1] *Research Scholar, Department of CSE, SECAB IET, Vijayapur, Visvesvaraya Technological University, Belgaum, Karnataka, India*
Faculty -ATS Sanjay Bhokare Group Of Institutes Miraj.
chandrakant.divate@gmail.com
[2] *Department of CSE, SECAB IET, Vijayapur, Visvesvaraya Technological University, Belgaum, Karnataka, India*
reachquadri@yahoo.com
[3] *Associate Professor, Department of Mathematics, Sri Sai Ram Engineering College, Chennai, Tamil Nadu*
sumathi.math@sairam.edu.in
[4] *Professor, Department of Biomedical Engineering, Dhanalakshmi Srinivasan College of Engineering, Coimbatore*
praniraji1@gmail.com
[5] *Assistant Professor, Department of Computer Science & Engineering, Graphic Era Deemed to be University, Dehradun, Uttarakhand*
hemantsinghpokhariya@geu.ac.in
[6] *Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, Tamilnadu*
**deepakarun@saveetha.com*
[7] *Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, Tamilnadu*
Anuragshri76@gmail.com

need for the preprocessing of biometric data. The multifaceted nature of biometric data in computerized systems has led to the development of sophisticated techniques in image processing and data mining. Particularly, classification algorithms within data mining operations have assumed greater prominence, playing a crucial role in the effective analysis and utilization of biometric data across a myriad of applications.

Specific to the classification an artificial neural network and fuzzy logic based algorithms are performing major roles. To obtain accurate results from such classifications, always there is a need of accurate real time data. As biometric input to such automated systems always requires powerful feature extractions mechanisms Numerous experiments are currently being conducted in the realm of image processing, focusing on the extraction of valuable features for a variety of applications, including person identification, gender identification, face recognition, facial expression recognition, ethnicity classification, and gesture recognition systems [31]. These endeavors represent a dynamic field where technological innovations are continually evolving to enhance the accuracy and efficiency of biometric applications. In the pursuit of person identification, gender determination, and various facial recognition tasks, image processing plays a pivotal role. Researchers and engineers are actively engaged in refining algorithms and methodologies to extract intricate details from visual data, enabling more robust and nuanced identification processes. The applications span a wide spectrum, from personalized security systems to advanced human-computer interaction technologies. Facial expression recognition, another facet of image processing exploration, involves the intricate analysis of facial features to discern emotional states accurately. The development of sophisticated algorithms enables systems to interpret subtle nuances in facial expressions, contributing to advancements in human-computer interaction, healthcare diagnostics, and other fields where understanding emotional cues is crucial. Moreover, ethnicity classification is a challenging yet crucial aspect of image processing research. Researchers are working on methodologies to accurately determine the ethnic origin of individuals based on facial features. This has implications in diverse fields, including demographic studies, market research, and personalized user experiences. Additionally, gesture recognition systems, a burgeoning area in image processing, involve the interpretation of hand movements and gestures for interactive computing. These systems find applications in diverse domains, from gaming and virtual reality to healthcare and smart home technologies. The significance of face and thumb recognition processes extends beyond image processing experiments, particularly in the domain of computer authentication. These processes serve as key components in safeguarding access to computer systems and sensitive information. Ongoing advancements in these authentication techniques contribute to the development of more secure and user-friendly systems, bridging the gap between cutting-edge technology and practical applications in computer security. Processes to function properly in the absence of an image processing system. The widespread availability of high-performance digital cameras and communication interfaces on the market has led to significant improvements in the efficacy and speed of image processing. These improvements have been made in recent years. The amount of money spent on processing photographs has gone down, and the overall quality of the programme has been improved [2].

Nonetheless, atomizing the industrial process comes with its own unique challenges to overcome. Both the performance of the central processing unit (CPU) and the ability to organise one's time effectively have become more important. The quality assurance and control processes are given the utmost priority in the manufacturing procedure. Throughout the whole production process, machines that are capable of making efficient use of computer vision are required to make component identification feasible.

Over the course of the last several years, industrial vision systems have already been the focus of a significant Till today, numerous successful developments have come out in the implementation of fingerprint identification systems. Now a days, an automation in fingerprint based gender recognition, as compared to other biometrics input, is the demanding research area since last decades. Gender classification involves categorizing a provided test image or video into one of two classes: either male or female, as delineated by sources [31], [32], and [3]. While a forensic expert may intuitively discern the gender of an individual, the automation of gender identification poses a significant challenge. In the contemporary landscape, gender recognition has found application in various domains such as E-commerce, E-Governance systems, forensic applications, and human-computer interaction, as highlighted in source [31]. Despite the simplicity with which a forensic professional may employ their expertise, automating this process requires sophisticated methodologies to navigate the complexities inherent in gender identification.

Generally, the most common stages of computerized classification systems are developed in two parts– training part and testing part. Both segments encompass pre-processing and feature extraction steps before embarking on the classification phase. Figure 1 illustrates the comprehensive steps involved in the classification process. The initial stages involve pre-processing, where raw data is refined and prepared for subsequent analysis. Following this, feature extraction focuses on identifying and extracting relevant patterns or characteristics from the processed data. These refined features then serve as input for the classification step, where the system categorizes or assigns labels based on the learned patterns. This structured approach ensures that the input data undergoes necessary transformations, enhancing the efficacy and accuracy of the subsequent classification process, as depicted in Figure 1.

1.1 Pre-processing:

The computerized fingerprint input image further undergoes to, pre-processing steps like, segmentation [33] [5], binarisation [34] [30] thinning [33] [17], orientation [4] [30]

1.2 Feature extraction:

After the pre-processing of fingerprint image, the system always proceeds for different features extraction step [33] [4] [34] [20] [28] [29] to form a combined feature vector. The feature vector is then recorded as dataset in database during the training part of system. This is the major step in any system as it provides maximum accuracy to an automated system, and this paper is highly focusing on this step.

1.3 Classification:

During the testing phase of an automated system, the combined feature vector derived from the test fingerprint image is subsequently input into an appropriate classifier. Various classifiers, such as Neural Network (NN) [33] [4] [34] [20], K-Nearest Neighbor (KNN) [22], Support Vector Machine (SVM) [1] [34], and others, are em-ployed for the purpose of obtaining the classified gender, specifically as either male or female. This step in the process involves leveraging the learned patterns and relationships within the feature vector to make accurate predictions and categorizations based on the chosen classification algorithm. The selection of an optimal classi-fier is crucial in ensuring the reliability and precision of the gender classification outcomes in the context of automated systems.

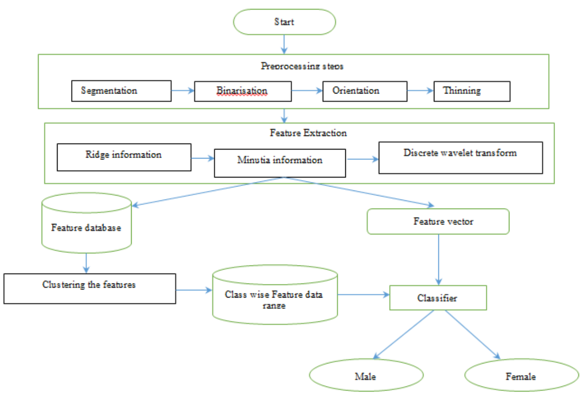

Fig 1: Input image

2. Review of Literature

This section presents the work done by other researchers related to feature extraction, fingerprint identification, fingerprint classification etc. In the review of literatures the authors proposed the different solutions of finger-print feature extraction.

Ashish Mishra et al. [1] elucidate that fingerprint recognition can be achieved through the analysis of parameters such as ridge count, ridge density, ridge thickness to valley thickness ratio, ridge dimension, and fingerprint patterns. According to the findings of Arun K.S. [25], each image within a database is characterized by a feature vector, comprising values for ridge thickness to valley thickness ratio (RTVTR) and ridge density. These studies underscore the significance of specific fingerprint attributes and their quantitative measures in the recognition process, demonstrating the diverse approaches and parameters considered by researchers in the field of fingerprint recognition. Roli Bansal et al [26] revels on minutiae counts, ridge end count and bifurcation count features. Ramandeep Kaur et al [27] has been introduced a method for finding ridges endpoint and bifurcation point in the fingerprint image. P. Gnanasivam et al [28] revels on Fingerprint Orientation Estimation, Orientation Angle Identification, and vertical Orientation. Eyüp Burak CEYHAN et al [20] focuses on ridge counts, ridge thickness only. Ronny Merkel et al. [2] introduce a comprehensive set of features for fingerprint analysis, encompassing binary pixels, mean print gray value (F2), standard deviation (F3), mean variance (F4), gradients (F5) of local image regions, image roughness (F6), and coherence (F7). Additionally, their investigation introduces novel features, including Tamura contrast, features based on Benford's Law [15] (F9 - F18, representing the relative digit frequency of the first digit (0 - 9) of image pixel gray values), and a newly explored dust feature (F19).

On a related note, Prabha et al. [3] adopt a different approach by applying two-dimensional DWTto the input image of a fingerprint. This process results in an image representation characterized by low-high, high-low, and high-high sub-bands, representing three distinct details: horizontal, vertical, and diagonal. The approximation of these details is presented in the low-low sub-band. This utilization of wavelet transform adds a layer of complexity and detail to the analysis of fingerprint images, providing a different perspective on feature extraction and representation in comparison to the methods employed by Merkel et al. [2]. A. S. Falohun et al [10] considers RTVTR features. Shivanand Gornale et al. [11] propose a methodology that employs features derived from both DWT and Gabor-based techniques to extract gender information from fingerprints, facilitating the classification of individuals as male or female. Himanshi et al. [12] focus on the combined use of DWT and Principal Component

Analysis (PCA) for feature extraction in their study. Suchita Tarare et al. [15] utilize DWT, where the wavelet serves as the basis function, extracting energy-based features from an image. Mangesh K. Shinde et al. [16] leverage both DWT. and Singular Value Decomposition (SVD) in their feature extraction process, emphasizing the significance of these techniques in enhancing the discriminative power of extracted features. Suman Sahu et al. [17] concentrate on the extraction of key features such as Ridge Valley Area (RVA) and Frequency Domain Analysis, incorporating horizontal, vertical, diagonal, and amplitude-based features. These diverse approaches highlight the versatility of feature extraction techniques, showcasing the amalgamation of wavelet-based methods, frequency domain analysis, and other advanced methodologies in the realm of fingerprint gender classification.

D. Gnana Rajesh et al. [21] adopt DWT. for the analysis of fingerprints, emphasizing the efficacy of this technique in capturing essential features. Ms. Bindhu K. Rajan et al. [22] concentrate on Ridge Thickness to Valley Thickness Ratio (RTVTR) as a pivotal feature extracted from fingerprint images. P. Gnanasivam et al. [24] leverage a combination of DWT. and Singular Value Decomposition (SVD) for feature extraction in their research, highlighting the versatility of these methods. S. Sivaranjani et al. [18] focus on minutiae extraction for fingerprints and Principal Component Analysis (PCA) features for footprint analysis. Satyabrata Swain et al. [23] introduce an extraction technique for two extended features, namely dots and incipient ridges, achieved through the tracing of valleys. E.O. OMIDIORA et al. [29] analyze Ridge Thickness to Valley Thickness Ratio (RTVTR) and Ridge Count features as significant contributors to gender identification. Yi-Pin Hsu et al. [5] direct their attention to feature extraction based on Modified Haar, introducing a unique approach to capturing essential fingerprint characteristics. Paramvir Singh et al. [19] delve into the minutiae points detection feature as a focal point of their study, highlighting its relevance in fingerprint analysis. S. Revathi et al. [14] explore various features including ridge count, ridge length, ridge curvature direction, and ridge type, contributing to a comprehensive understanding of fingerprint characteristics. These diverse studies showcase the breadth of methodologies and features considered in the field of fingerprint analysis and gender identification.

Unhale A.A et al. [13] focus on ridge features and conventional minutiae features, including minutiae type, orientation, and position, as essential elements extracted from fingerprints in their research. Ritu Kaur et al. [9] propose a gender estimation method by analyzing fingerprints using Fast Fourier Transform (FFT), Discrete Cosine Transform (DCT), and Power Spectral Density (PSD) techniques. Samta Gupta et al. [8] employ wavelet transformation for the extraction of fingerprint characteristics, conducting decomposition up to five levels to capture nuanced details in their study. Heena Agrawal et al. [7] utilize features such as ridge thickness, ridge density, and ridge-to-valley thickness ratio (RTVTR) to characterize fingerprints. Rijo Jackson Tom et al. [6] aim to enhance fingerprint analysis by incorporating 2D DWT. and Principal Component Analysis (PCA) features, providing a multifaceted approach to feature extraction. These diverse approaches showcase the breadth of techniques applied to fingerprint analysis, reflecting the continuous exploration and integration of various methods to enhance the accuracy and reliability of gender estimation from fingerprint data.

With literature review on features, the features those are considered in most of the research are, ridge count, ridge end point, ridge bifurcation count, RTVTR, DCT, DWT, PCA, FFT, PSD etc.

Even though feature extraction techniques are precise and powerful, the results of gender classification based on these features are still approximate to match towards gender identification. Hence it is required to perform on the research work of other types of feature extraction that will obtain the accurate result of gender classification from fingerprint.

3. Methodology Used

In the realm of fingerprint analysis, the process of feature extraction is a crucial step that must be executed both during fingerprint training and testing phases. The feature extraction steps undertaken in both these stages play a pivotal role in capturing the distinctive characteristics of fingerprints. The key steps involved in fingerprint feature extraction during both training and testing phases are outlined as follows:

3.1 DWT:

The extraction of fingerprint features is accomplished through the utilization of DWT., employing the Daubechies-wavelet, specifically the Daubechies-tab 4 filter. The decomposition process follows the Mallat-tree decomposition algorithm. Subsequently, wavelet statistical features, including the mean and standard deviation of the approximation, are extracted using Equations (1) and (2) respectively. These extracted features are then systematically stored in a features library, forming a comprehensive repository of essential fingerprint characteristics for further analysis.

$$Mean(M) = \frac{1}{N^2} \sum_{i,\ j=1}^{N} p(\,i, j\,) \;\ldots.(1)$$

$$Standard\ Deviation(sd) = \sqrt{\frac{1}{N^2} \sum_{i,\ j=1}^{N} [\,p(\,i, j\,) - M]^2} \;\ldots.(2)$$

The DWT. operates in a manner analogous to a hierarchical sub-band system, where the sub-bands are arranged in a logarithmically spaced frequency structure, resembling an octave-band decomposition. The image undergoes decomposition, essentially being divided into four sub-bands and critically subsampled through the application of DWT, as illustrated in Figure 2(a). These sub-bands are denoted as LH1, HL1, and HH1, representing the finest scale wavelet coefficients, i.e., detail images. Simultaneously, the sub-band LL1 corresponds to the coarse-level coefficients, i.e., the approximation image.

To further obtain the next level of coarse-level wavelet coefficients, the sub-band LL1 is exclusively subjected to another round of decomposition and critical sampling. This process results in a two-level wavelet decomposition, as depicted in Figure 2(b). The successive stages of decomposition enable the extraction of increasingly detailed information from the original image, providing a multi-resolution representation that captures both finer details and the overall structure of the image.

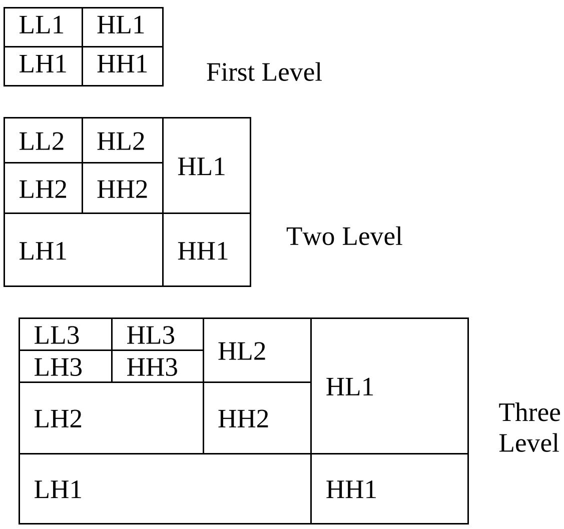

Fig.2 Thumb image decomposition structure

Similarly, to obtain next three-level wavelet decomposition, LL2 image will be used as shown in Figure 2(c). Also Figure 3 represents three-level wavelet decomposition. The decomposition process continues iteratively until reaching the final scale. At each level of decomposition, detailed sub-bands of the images are computed as features. These features, extracted from the wavelet-transformed images, serve as valuable inputs for fingerprint gender classification and identification. Extending this process, features up to the k-level sub-bands are computed and systematically stored in the features library, where k takes values from 0 to an arbitrary level, contributing to an enhanced correct matching rate. Furthermore, an additional proposal involves the computation of co-occurrence matrix features specifically for the detail sub-bands of 1-level DWT decomposed images, namely LL1, LH1, HL1, and HH1. These co-occurrence features, referred to as wavelet co-occurrence features, encompass metrics such as contrast, energy, entropy, local homogeneity, cluster shade, cluster prominence, and maximum probability. The computation of these features involves utilizing equations (3) to (16), providing a comprehensive set of metrics derived from the co-occurrence matrix C(i, j). This approach aims to enrich the feature set, enhancing the discriminative power and information content for improved performance in fingerprint analysis and classification

$$\text{Contrast} = \sum_{i,j=1}^{N} (i-j)^2\ C(i,j) \ldots\ldots(3)$$

$$\text{Energy} = \sum_{i,j=1}^{N} c^2\,(\text{i}, \text{j}) \ldots\ldots\ldots\ldots\ldots\ldots(4)$$

$$\text{Entropy} = \sum_{i,j=1}^{N} c\,(\text{i}, \text{j})\ log_2\ \text{c}(\text{i}, \text{j}) \ldots\ldots\ldots..(5)$$

$$\text{Local Homogeneity} = \sum_{i,j=1}^{N} \frac{1}{1+(i-j)^2}\ c(i,j) \ldots.(6)$$

$$\text{Cluster Shade} = \sum_{i,j=1}^{N} \left(i - M_x + j - M_y\right)^2 c(i,j) \ldots.(7)$$

$$\text{Cluster prominence} = \sum_{i,j=1}^{N} \left(i - M_x + j - M_y\right)^4 c(i,j) \ldots.(8)$$

$$\text{Information measure of correlation} = \frac{\left(Entropy - H_{xy}\right)}{\max\left(H_x, H_y\right)} \ldots\ldots(9)$$

Where,

$$\text{M}_x = \sum_{i,j=1}^{N} i\ C(i,j) \ldots\ldots(10)$$

$$\text{M}_y = \sum_{i,j=1}^{N} j\ C(i,j) \ldots\ldots(11)$$

$$H_{x,y} = -\sum_{i,j=1}^{N} C(i,j)\ log\left(S_x(i)S_y(j)\right) \ldots..(12)$$

$$H_x = -\sum_{i,j=1}^{N} S_x(i)\ log\left(S_x(i)\right) \ldots..(13) H_y$$

$$= -\sum_{i,j=1}^{N} S_y(j)\ log\left(S_y(j)\right) \ldots(14)$$

$$\mathrm{S}_x(\mathrm{i}) = \sum_{j=1}^{N} C(i,j) \ldots..(15) \quad \mathrm{S}_y(\mathrm{j})$$

$$= \sum_{i=1}^{N} C(i,j) \ldots..(16)$$

In this context, the fingerprint images undergo a decomposition process utilizing DWT. Subsequently, a consistent set of statistical wavelet features and co-occurrence matrix features is extracted from the decomposed images. This methodology ensures that a standardized and comprehensive feature set is obtained from the fingerprint images, incorporating both the statistical characteristics derived from wavelet analysis and the spatial relationships captured by co-occurrence matrices. The combined feature set contributes to a robust representation of the fingerprint images, enabling effective gender classification and identification processes based on the extracted features.

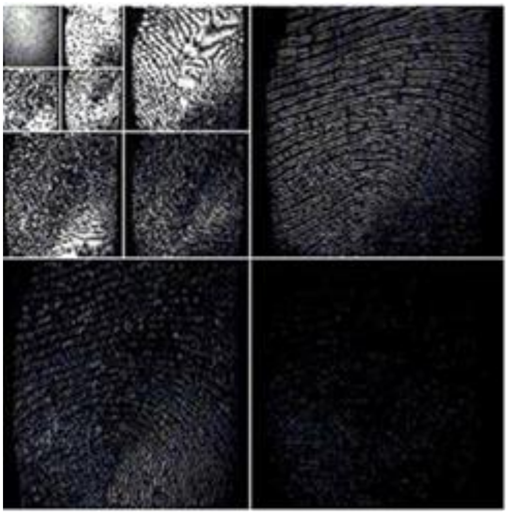

Fig.3: Decomposition of thumb image upto 3-Level

3.2 Algorithm-DWT: The various steps involved in the DWT feature extraction algorithm are as follows,

1. Image Processing:

- Read an image of a fingerprint.
- Convert the image to grayscale.
- Resize the image to dimensions 256×256.
- Apply preprocessing techniques to enhance image quality.
- Store the preprocessed image as a variable.

2. Evaluate Fingerprint Mean Value:

- Calculate the mean value (Fm) of the pixels in the preprocessed fingerprint image using the formula, Fm = F - μ, where μ represents the mean value.

3. Apply DWT

- Apply conventional DWT on Fm.
- Represent the DWT-transformed image as FDWT.
- Determine the concentration vector CDWT from FDWT.

4. Select Top Coefficients based on Energy Content:

- Extract the top 5% coefficients of FDWT, onsidering their energy content.
- Identify the corresponding elements in CDWT as CDWTi.
- Retrieve the index values i associated with these coefficients from CDWT.

5. Plot Characteristics of the Fingerprint:

- Plot CDWTi vs. i.
- The resulting curve provides the unique characteristics of the fingerprint, showcasing the distribution and significance of the selected coefficients in the context of energy content.

3.3 Finding the Ridge Information (RI) Features:

In the automated biometric process of finger scanning, a ridge refers to a discernible curved line present in a finger image. These ridges constitute continuous curves across the fingerprint, providing a distinctive pattern for identification. Additionally, certain ridges terminate at specific points known as ridge endings, marking the conclusion of their course. Moreover, in some instances, two ridges may converge at a particular point, forming a distinctive pattern called a bifurcation. This intricate network of ridges, endings, and bifurcations collectively constitutes the unique and intricate fingerprint pattern, crucial for accurate and reliable biometric identification processes. In this paper we emphasis on the algorithm that helps to find features like Ridge Count (RC), Ridge Length (RL), Minimum Ridge Length (Min-RL), Maximum Ridge Length (Max-RL), Sum of all ridge length=Sum-RL, Average Ridge Length (Avg-RL).

Algorithm Ridge Information (RI) Features: The following is the algorithm that extracts the above noted features,

```
1. Read fingerprint image, convert to grayscale, and
   resize as 256×256. Apply preprocessing and store as
   variable P.
2. Find thinned image and store as FThin.
3. Set RC=0, RL=0, Min-RL=0, Max-RL=0, Sum-
   RL=0, Avg-RL=0. // Set initial values of ridge
   properties to zero.
4. For x = 1 to 256 step 1
   a. For y = 1 to 256 step 1
      i. if (P(x, y) == BLACK) then
         // Ridge identified, trace the ridge till it terminates.
         RC = RC + 1
         RL = 1

         For i = x to 256 step 1
            For j = y to 256 step 1
               // Terminate the ridge by turning pixels to
                  WHITE as it is traced.
               P(i, j) = WHITE
               Flag = 0
               // Check neighboring pixels for continuation
                  of the ridge.
               if (j+1 < 256 and P(i, j+1) == BLACK) then
                  j = j + 1, flag = 1
               Else if (i+1 < 256 and j+1 < 256 and P(i+1,
                     j+1) == BLACK) then
                  i = i + 1, j = j + 1, flag = 1
               Else if (i+1 < 256 and P(i+1, j) == BLACK) then
                  i = i + 1, flag = 1
               Else if (i-1 > 1 and j+1 < 256 and P(i-1, j+1)
                     == BLACK) then
                  i = i - 1, j = j + 1, flag = 1
               Else if (i-1 > 1 and P(i-1, j) == BLACK) then
                                                  Continued…

                  i = i - 1, flag = 1
               Else if (i-1 > 1 and j-1 > 1 and P(i-1, j-1) ==
                     BLACK) then
                  i = i - 1, j = j - 1, flag = 1
               Else if (j-1 > 1 and P(i, j-1) == BLACK) then
                  j = j - 1, flag = 1
               Else if (i-1 > 1 and j-1 > 1 and P(i-1, j-1) ==
                     BLACK) then
                  i = i - 1, j = j - 1, flag = 1
               End if
            End for
            // Update ridge length and check for termination.
            If (flag == 0) then
               If (x == 1 and y == 1) then
                  Min-RL = RL, Max-RL = RL
               End if
               If (Min-RL > RL) then Min-RL = RL
               If (Max-RL < RL) then Max-RL = RL

               Sum-RL = Sum-RL + RL
               Go to step b
            Else RL = RL + 1
            End if
         Next j
      End if
   b. Next y
5. Next x

6. Avg-RL = Sum-RL / RC

7. Store Ridge Information (RI) - Ridge Count (RC), Ridge
   Length (RL), Minimum Ridge Length (Min-RL),
   Maximum Ridge Length (Max-RL), Sum of all ridge
   length = Sum-RL, Average Ridge Length (Avg-RL) in
   the database.
8. End Of Algorithm
```

3.4 Finding the Minutia Information:

Minutiae, encompassing ridge endings and bifurcations, stand as pivotal features within a fingerprint image. These distinctive minutiae points play a crucial role in determining the uniqueness of a fingerprint, acting as the fundamental characteristics that define its individuality.

The quantity of minutiae within a high-quality fingerprint image typically ranges between 25 and 80, contingent upon factors such as the resolution of the fingerprint scanner and the precise positioning of the finger on the sensor.

Minutiae points are precisely defined as the locations where ridge lines either terminate or bifurcate. They serve as local ridge discontinuities, and their abundance and types contribute significantly to the fingerprint's overall uniqueness. The various types of minutiae points are elucidated below and visually represented in Figure 4 for a comprehensive understanding.

a. Ridge Ending: This occurs when a ridge abruptly terminates, creating a distinct point where the ridge concludes.

b. Ridge Bifurcation: This refers to the juncture where a single ridge undergoes a branching pattern, leading to the emergence of two or more separate ridges.

c. Ridge Dots: These are extremely minute ridges, often characterized by their diminutive size within the fingerprint pattern.

d. Ridge Islands: Slightly elongated compared to dots, ridge islands find themselves situated between two diverging ridges, marking an intermediate spatial presence.

e. Ponds or Lakes: These are the vacant spaces between two diverging ridges, forming an empty expanse within the fingerprint pattern.

f. Spurs: Spurs manifest as notches protruding from a ridge, contributing to the intricacies of the fingerprint's topographical features.

g. Bridges: These are diminutive ridges that serve to connect two longer adjacent ridges, forming a bridge-like structure within the fingerprint.

h. Crossovers: Formed at points where two ridges intersect and cross each other, crossovers add an additional layer of complexity to the overall fingerprint

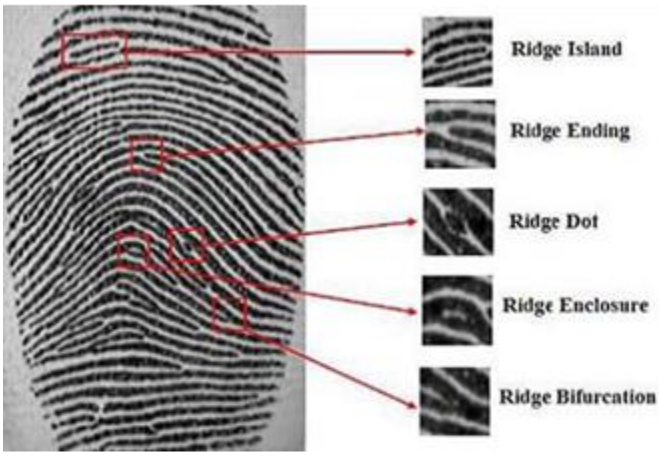

Fig.4: Minutia types information

Ridge endings and ridge bifurcations stand out as the most frequently employed minutia types, primarily because all other minutiae variants stem from combinations of these two fundamental types. The algorithm outlined below encapsulates the standard steps involved in computing various minutiae patterns, including Ridge Bifurcation Count (RBC), Ridge End Count (REC), and Minutia Count (μC).

Algorithm Minutia Information (μI): The steps involved in the Minutia Information (μI) feature extraction algorithm are as follows,

1. Read fingerprint image, convert to grayscale, resize to 256×256, apply preprocessing, and store as variable P.

2. Find thinned image and store as FThin.

3. Set RBC=0, REC=0, μC=0, ang=0 // Initialize ridge properties.

4. Initialize stack_xy[65536], temp_xy[100] // Initialize stacks.

5. top = -1 // Initialize stack top.

6. For x = 1 to 256 step 1

 a. For y = 1 to 256 step 1

  i. if (P(x, y) == BLACK) then

   // Ridge identified, trace the ridge till it terminates.

   RC = RC + 1

   For i = x to 256 step 1

    For j = y to 256 step 1

     // Terminate the ridge by turning pixels to WHITE as it is traced.

     P(i, j) = WHITE

     Flag = 0

     // Check neighboring pixels for continuation of the ridge.

```
// ... (similar to previous algorithm)
// Process ridge continuation and termination.
If (flag == 0) then
  REC = REC + 1
  Go to step b
Else if (flag > 1) then
  POP_stack_xy(px, py, c)
  While (stack_top != -1)
    If (px != i and py != j) then
      PUSH_temp_xy(px, py, c)
      POP_stack_xy(px, py, c)
    Else
      While (temp_top != -1)
        PUSH_stack_xy(px, py, c)
        POP_temp_xy(px, py, c)
      End_while
      break
    End if
  End_while
  If (stack_top == -1) then
    RBC = RBC + 1
    While (temp_top != -1)
      POP_temp_xy(px, py, c)
      PUSH_stack_xy(px, py, c)
    End_while
    PUSH_stack_xy(i, j, flag)
  End if
End if
Next j
Next i
End if
b. Next y
7. Next x
8. μC = REC + RBC
9. Store Minutia Information - Ridge bifurcation count
   (RBC), Ridge end count (REC), Minutia count (μC)
   in the database.
10. End of Algorithm.
```

4. Data Set

The proposed feature extraction algorithms were evaluated using fingerprint images sourced from the FVC2004 DB1 database and an internal database. Specifically, the FVC2004 DB1A database comprises 150 fingers in width, with 12 samples per finger in depth, resulting in a total of 1800 fingerprint images. In the context of performance evaluation, the fingerprints within the same database were matched against each other. The FVC2004 DB1A database images are of 8-bit gray level and possess a resolution of 400x560 pixels, totaling 224,000 pixels (224 Kpixels). On the other hand, the internal database fingerprints were collected using the Fingkey Hamster II scanner manufactured by Nitgen Biometric Solution, Korea. These internal database images are also 8-bit gray level, with a different size of 260x300 pixels and a resolution of 500 dots per inch (dpi). It's noteworthy that the internal database fingerprints encompass a diverse representation, being sourced from individuals irrespective of gender and age. Furthermore, the data collection process for the internal database involved capturing fingerprints without imposing any restrictions on finger position, pressure on the scanner, or specific orientations. Each individual contributed scans of all 10 fingers, adding to the richness and variability of the dataset [30].

5. Experimental Results

The algorithms implemented for fingerprint extraction are used to read the features from fingerprint images, the experimental readings with testing fingerprint images scanned by scanner are represented in following Tables 1 for ridge information, Table 2 represents the minutia information, and Table 3 shows the DWTresults from level 1 to level 6. The readings are taken for tem fingers of person.

Table 1: Ridge information of a person fingerprints

Finger Name	Max-RL	Min-RL	Avg-RL	Ridge count
Left Thumb	16.49	16.49	0.19	178
Left Index Finger	16.12	16.12	0.20	164
Left Middle Finger	16.12	16.12	0.23	143
Left Ring Finger	16.49	16.49	0.25	133
Left Little Finger	16.12	15.23	0.22	142
Right Thumb	16.49	16.49	0.17	193
Right Index Finger	16.12	16.12	0.20	162
Right Middle Finger	15.62	15.62	0.21	151
Right Ring Finger	16.12	16.12	0.21	156
Right Little Finger	15.62	15.62	0.20	159

Table 2: Minutia information of a person fingerprints

Finger Name	Minutia Count	Bifurcation count	Ridge end count
Left Thumb	41	3	38
Left Index	53	11	42
Left Middle	28	6	22
Left Ring	50	5	45
Left Little	53	5	48
Right Thumb	47	6	41
Right Index	53	4	49
Right Middle	39	5	34
Right Ring	86	6	80
Right Little	60	5	55

Table 3: Ridge information of a person fingerprints

Finger Name	DWT L1	DWT L2	DWT L3	DWT L4	DWT L5	DWT L6
Left Thumb	1551.65	7.82	3.91	2.22	1.55	2.81
Left Index	1574.00	19.00	9.50	3.00	1.11	0.37
Left Middle	1567.60	15.80	7.90	2.95	1.00	0.41
Left Ring	1589.65	26.82	13.41	6.90	3.29	3.04
Left Little	1555.44	9.72	4.86	5.48	3.34	2.82
Right Thumb	1536.00	0.00	0.00	10.44	6.76	6.67
Right Index	1536.00	0.00	0.00	0.00	0.00	0.00
Right Middle	1583.98	23.99	11.99	4.31	1.53	0.59
Right Ring	1594.73	29.36	14.68	4.31	1.46	0.51
Right Little	1599.98	31.99	15.99	4.26	1.19	0.63

6. Conclusion

In this paper, a novel algorithm has been proposed with the primary aim of enhancing the performance of classification, identification algorithms, and overall fingerprint analysis. The approach employed in this research involves the utilization of efficient algorithms, specifically focusing on line (ridge)-based techniques through local component analysis for performance evaluation. Minutiae extraction, a critical aspect of fingerprint analysis, is conducted using global component analysis applied to fingerprint images. The results obtained from this proposed method showcase a remarkable minutiae information extraction accuracy of approximately 98.03%, demonstrating a high level of fidelity with the original input images. Moreover, the algorithm achieves successful detection of ridge information across the entire fingerprint, achieving an accuracy rate of 93.07%. The utilization of DWT on fingerprint images further enhances the precision, with an impressive accuracy level of 94.65%. Continuing with this research, efforts are underway to address and eliminate existing limitations in the algorithms. These ongoing endeavors are directed towards reducing computation time and costs, ultimately striving to provide improved accuracy in fingerprint analysis. The overarching goal is to advance the state-of-the-art in fingerprint recognition systems by addressing current challenges and enhancing the overall efficiency of the proposed algorithms.

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