

A New Fingerprint Enhancement Approach Using Image Fusion of Histogram Equalisation and Skeleton

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Abstract—Fingerprint classification is a technique used to assign fingerprints into five established classes namely Whorl, Left loop, Right loop, Arch and Tented Arch based on their ridge structures and singular points' trait. Although some progresses have been made thus far to improve accuracy rates, problem arises from ambiguous fingerprints is far from over, especially in large intra-class and small inter-class variations. Poor quality images including blur, dry, wet, low-contrast, cut, scarred and smudgy, are equally challenging. As a good start of work, fingerprint image enhancement has been focused on this study. It begins with greyscale normalization, followed by histogram equalization, binarization, skeletonization and ends with image fusion, which eventually produces high quality images with clear ridge flows. 27,000 fingerprint images acquired from The National Institute of Standard and Technology (NIST) Special Database 14, which is de facto dataset for experimental in this study. With the multi-type enhancement method, the fingerprint images became clearly visible.

Index Terms—Binarization; Fingerprint; Histogram Equalization; Skeletonization.

I. INTRODUCTION

Biometrics are measurable characteristics based on physiological and behavioural traits that are used in the identification of individuals. The most important type of human biometrics is fingerprints. Fingerprints have been used for personal recognition in forensic applications such as criminal investigation tools and in civilian applications, as well as border access control systems, national identity card validation and authentication processors. The uniqueness and immutability of fingerprint patterns as well as the low cost of associated biometric equipment make fingerprints more desirable than the other types of biometrics [1]. Fingerprints develop during the fourth or the fifth month after conception. The pattern of a person's fingerprints remain much the same until his death, or until he gets injured in an accident. Age of a person does not change a person's fingerprints but injury does. Schaeuble [2] and Babler [3] had proven that fingerprints of twins sharing similar DNAs are different. Fingerprint biometric identification is low-cost because it involves pattern recognition using IT equipment and does not require laboratory wet tests (such as blood test) [4].

In fingerprint identification, both matching accuracy and processing time are critical issues. To achieve an efficient identification of a fingerprint, fingerprints in the database are organized into a number of mutually exclusive classes that

share certain similar properties. This process is called fingerprint classification. In order to design an automatic system for identification which has better accuracy, pre-processing of the fingerprints have to be carried out to enhance and extract the fingerprint features [5].

II. BACKGROUND

Automatic fingerprint classification techniques have been widely investigated during the last decade. Over the years, a number of different fingerprint classification techniques have been developed using myriad classification approaches and datasets. Each classification method has its own specific characteristics that researchers capitalize on to advance fingerprint classification research using a particular dataset. In order to design a more reliable automatic identification system, pre-processing of fingerprints has to take place in order to enhance and extract fingerprint features [7]. According to [1], most existing fingerprint classification approaches are based on global features including ridge orientation fields and singularities. Bazen and Gerez [8] found that accurate classification of fingerprints is highly dependent on the orientation fields' estimation and singular points detection algorithms.

The classification of fingerprint images is highly dependent on clear fingerprint images and the ability to accurately separate the foreground from the background. In order to obtain clear fingerprint structure shapes, it is necessary to improve the quality of the original fingerprint images, and to optimally extract the foreground from the background.

This study will focus on National Institute of Standard and Technology (NIST) special fingerprint database 14. This system will be tested using a standard dataset testing platform, employing grey-scale fingerprint images. The database contains 54,000 8-bit grey-scale images of rolled fingerprint impressions that were scanned from 27,000 individuals. This study uses the latest work of [9] as a baseline which has already shown results superior to those of [1] work. Identical fingerprint samples (f0000001 to f0027000 prints) that were used by [9] will also be used for all tests in this study. In order to confirm the improved performance of this system, scarred prints will also be included.

Regards of the issue above, the objective of this study is to improve the quality of defective images in the fingerprint dataset by using improved reconstructive enhancement techniques. It is hoped that the proposed fully automated

fingerprint classification system AFCS will overcome the challenges of existing fingerprint classification as a consistently reliable biometric system.

The AFCS may do so by reducing ambiguity error, minimize problems associated with poor quality images, and large intra-class variation. Existing fingerprint classification studies have shown some encouraging results with success rates greater than 94 percent. However, these results, as well as employed methods are disputable because the datasets used were from NIST 4 which contains fingerprint patterns that have already been cleaned and any existing noise removed from the background. In industrial and forensic applications the fingerprints that are collected are naturally flawed. For that reason, more rigorous testing using a higher level dataset such as the NIST Special fingerprint database 14 is necessary to confirm that a more elaborate procedure can be used effectively for industrial and forensic purposes. Manual processes are time consuming and tedious and less suitable for a real life applications.

III. NIST SPECIAL DATABASE 14

NIST Special Database 14, version 2, hereinafter is termed as NIST 14, created by the National Institute of Standard and Technology of the United States of America, is a database which contains 54,000 8-bit gray-scale images obtained by the rolled method of fingerprint acquisition, scanned from 27,000 fingers. NIST 14 is the standard dataset used by most researchers of fingerprint identification and classification systems. Using NIST 14, it is possible to access individual fingerprints that are representative of the natural distribution of human fingerprints in the population. Blue [10] and Jain et al. [11] found that the distribution of fingerprint classes in the population is not uniform. The frequencies of arch, tented arch, left loop, right loop, and whorl are approximately 3.7%, 2.9%, 33.8%, 31.7%, and 27.9% respectively, as shown in Figure 1. Therefore, it is important to use a suitable dataset with a large enough sample size that is representative of the natural distribution of human fingerprint classes in the population.

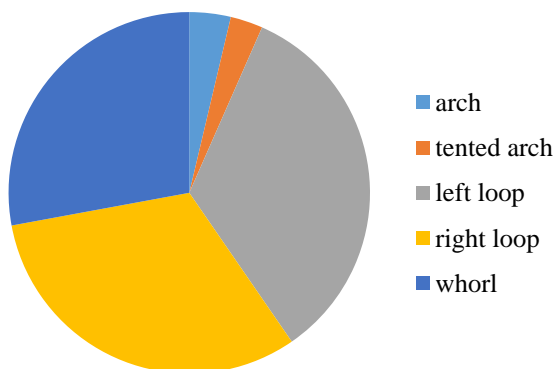


Figure 1: Representation of the human fingerprint class distribution

The fingerprints in the NIST 14 are stored and compressed using the wavelet scalar quantization (WSQ) compression specification. Fingerprint classes and other information such as sex and scan type are stored in a comment field in WSQ compressed file header. Classes in the WSQ file are true classes based on human expert classification, allowing for comparison with hypothesized or experiment classes.

IV. FINGERPRINT IMAGE ENHANCEMENT

Against the backdrop of the state-of-the-art classification drawbacks[1], this study, therefore, proposes a new fingerprint classification scheme with an aim to produce a high performance automatic fingerprint classification system. In order to achieve the goal a new set of techniques is introduced namely, image enhancement, segmentation, orientation field estimation, singular point detection and classification. Hereinafter, the first two processes are referred to as pre-processing while remaining is called post-processing.

Preciseness of fingerprint classification is highly dependent on both quality of fingerprint structure shapes and accuracy of fingerprint singular points. For that reasons, it is utmost important to improve the quality of the original fingerprint images, and to optimally extract the foreground from the background prior to post-processing.

In order to develop a high performance Automatic Fingerprint Classification System, image quality is a key factor. Fingerprint image samples are often distorted by smudges or blotches. In poor quality fingerprint images, the valleys and ridges are not clear and discontinuities exist in the ridges and are often caused by random interference in the capturing devices [12]. Overcoming the problems related to extreme contrast conditions (low contrast or high contrast) and associated discontinuities of the fingerprint patterns is a challenge. Therefore, it is necessary to apply fingerprint image enhancement before any classification procedure [13].

In this study, fingerprint images were normalized by using grayscale normalization (detailed in section A: Grey-Level Normalization) to standardize the intensity of the pixels, and the contrast of the images were improved using Histogram Equalization (detailed in section B: Contrast Enhancement). To solve the problem of discontinuity, Binarization and Skeletonization approaches were applied (detailed in section C: Binarization and section D: Skeletonization). In the final step, Fusion algorithms were applied to the output image, and with the help of Skeletonization and Histogram Equalization, enhanced the quality of fingerprint images (refer to Figure 2).

A. Grey-Level Normalization

Pixel intensity values of fingerprint images of one part of an image may differ from that of another part due to the sensitivity of the capture device with respect to the temperature and also environmental illumination. The intensity values of the grayscale images are normally between 0 and 255. The values of the grayscale from 0 to 128 are considered lower-range, which typically results in dark images (under-exposure). The upper-range of the greyscale levels, with values from 128 to 255, refers to the bright part of the images (over-exposure). In order to capture an image with uniform characteristics, and to remove the noise that is introduced by the sensor, as well as limiting the variation in grey-level values along the ridges and valleys, a normalization technique needs to be applied.

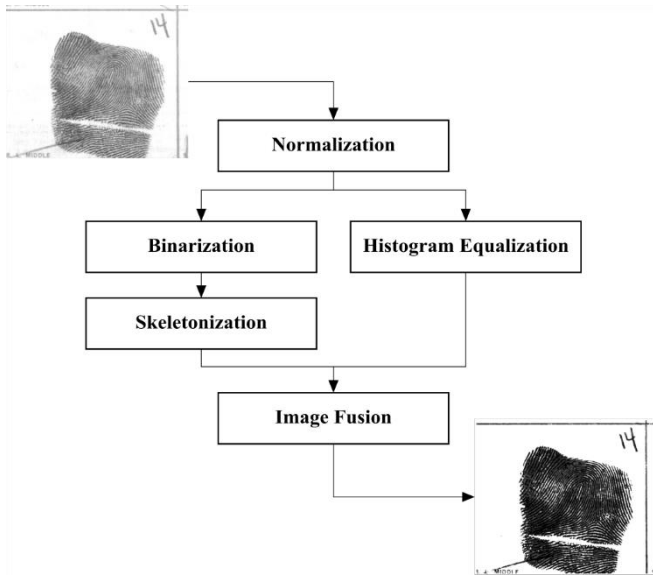


Figure 2: The proposed enhanced fingerprint image technique.

The grayscale normalization technique is a process used to standardize the intensity level of pixels in an image by adjusting the range of grey-level values. It does so by using the statistical parameters of mean and variance. The Normalization method proposed by [14] is adopted in this study due to its efficiency and simplicity. The method consists of three steps: In the first step, a global mean value of the fingerprint image is determined. In the second step, the global variance value of the fingerprint image is computed. In the final step, new intensity values are calculated.

Normalization is a pixel-wise operation that does not change the clarity of the ridge and valley structures. Even if normalization is performed on the entire image, this process cannot compensate for the intensity variations in different parts of the image due to finger pressure differences.

The Algorithm 1 as depicted in Figure 3 summarizes the normalization process in pseudo-code form. An example of a fingerprint image that has gone through the normalization process is provided in Figure 4.

```

Input: Fingerprint Image I of size W X H.
Output: Normalized Image N.
Begin:
  Set Sum ← 0
  for i = 1 → W, increment by 1 do
    for j = 1 → H, increment by 1 do
      Sum ← Sum + I(i, j)
    end for
  end for
  Mg ← Sum / (W * H) // Mg is global mean
  Set Sum ← 0;
  for i = 1 → W, increment by 1 do
    for j = 1 → H, increment by 1 do
      Sum ← Sum + SQR(I(i, j) - Mg);
    end for
  end for
  Vg ← Sum / (W * H) // Vg is global Variance
  Set Mg0 ← 127
  Set Vg0 ← 127
  for i = 1 → W, increment by 1 do
    for j = 1 → H, increment by 1 do
      if I(i, j) > Mg
        N(i, j) ← Mg0 + SQR(Vg0 * SQR(I(i, j) - Mg) / Vg)
      Else N(i, j) ← Mg0 - SQR(Vg0 * SQR(I(i, j) - Mg) / Vg)
      end if
    end for
  end for
End
  
```

Figure 3: Algorithm for Fingerprint image normalization

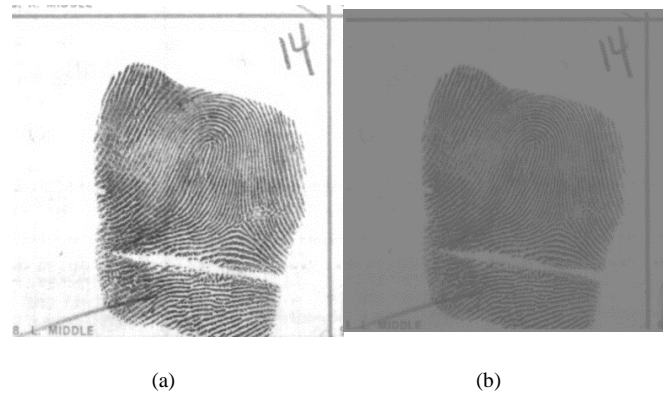


Figure 4: Grey-level normalization: (a) Original image (Source NIST database 14: f0000008; (b) Normalized image.

B. Contrast Enhancement

Although the Normalization process standardizes the intensity of the pixels, the problems with the image contrasts still have to be overcome. The image contrast problem can be classified as being either high contrast or low contrast. It is generally caused by impressions of the fingertip during an ink scan and the effect of illumination in a live scan. Therefore, a Histogram Equalization technique (HE) is applied which is considered the most common approach for improving the appearance of poor quality images. In this study, the method that have been used was adopted from the study of Hanoon [15]. A summary of the HE process in pseudo-code is given in Figure 5.

```

Input: Normalized Fingerprint Image N of size W X H.
Output: Histogram Equalized Image HE .
Begin:
  for i = 1 → W, increment by 1 do
    for j = 1 → H, increment by 1 do
      Stat[I(i, j)] ← Stat[I(i, j)] + 1;
    end for
  end for // stat is statistic of each gray level
  Set TotalSum ← (W * H);
  Set Sum[0] ← Stat[0];
  for i = 1 → 255, increment by 1 do
    Sum[i] ← Sum[i-1] + Stat[i];
  end for

  for i = 0 → 255, increment by 1 do
    Normalized[i] ← Sum[i] / TotalSum;
  end for

  for i = 0 → 255, increment by 1 do
    Final[i] ← Normalized[i] * 255;
  end for

  for i = 1 → W, increment by 1 do
    for j = 1 → H, increment by 1 do
      HE(i, j) ← Final[I(i, j)];
    end for
  end for
End
  
```

Figure 5: Algorithm for Histogram equalization

A significant contrast differences between the normalized histogram and the equalized one illustrate the effectiveness of the HE as a principal contrast enhancement tool. The result of the Histogram Equalization Enhancement will be grayscale image as illustrated in Figures 6 (a), Figure 6 (b), Figure 6 (c) and Figure 6 (d).

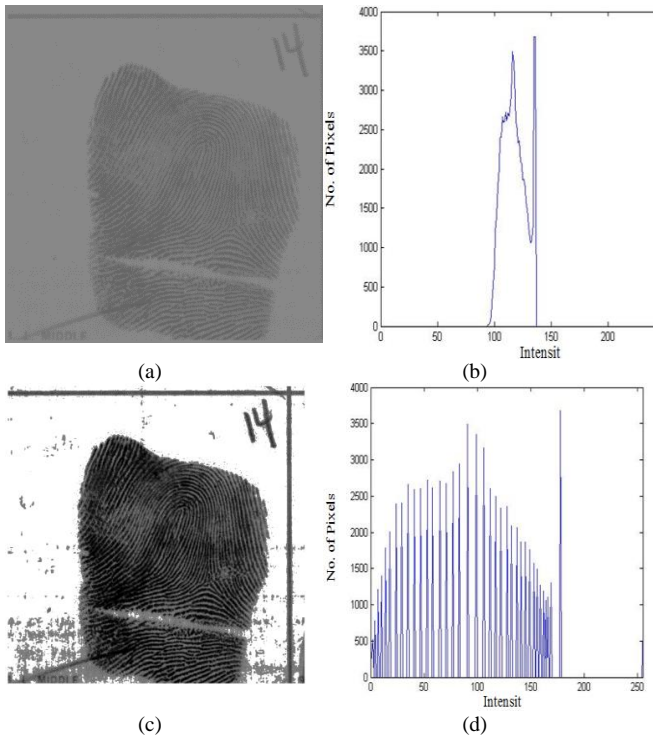


Figure 6: (a), (b) Normalized image with its histogram before HE, while (c), (d) are enhanced image after HE with its histogram.

C. Binarization

Binarization is a process that converts the grayscale image into binary form. A pixel value of 0 is assigned to the black area of the fingerprint image that represents the ridge lines, and a pixel value of 1 identifies the white area in the images that represents the valleys. The Binarization approach is used to keep the characteristics of the fingerprint ridge structure and to remove some of the cohesion between the patterns. The final result of Binarization is a clear image. In this study, the Binarization technique used is not static, so a dynamic calculation is performed on the threshold value to fill in any existing gaps and that method was adopted from the study of Fu et al. [16]. A summary of the Binarization process in pseudo-code form is given in Figure 7.

This algorithm shows a significant improvement of the ridge structure of the fingerprint image. The dynamic threshold value was used to remove the noise in the foreground of the fingerprint image as evidently illustrated in Figures 8 (a) and Figure 8 (b).

D. Skeletonization

The above binarization process converts fingerprint images into black dots which represent the ridges with a value of 0, while the white dots signify the valleys with a value of 1. On the hand, skeletonization (thinning) is a technique that is normally used on binarized images by reducing the thickness of a certain pattern shape until it is represented by 1-pixel wide lines. The method was used in this study, was adopted from the work of Kwon et al. [17].

The algorithm as shown in Figure 9 summarizes the Skeletonization process in pseudo-code form. An example of fingerprint image that has gone through the Skeletonization process is provided in Figure 10.

```

Input: Normalized Fingerprint Image N of size W X H.
Output: Binarized Image B.
Begin:
  for i= 1 → W, increment by 15 do
    for j= 1 → H, increment by 15 do
      Sum ← 0;
      for u= 1 → 15, increment by 1 do
        for v= 1 → 15, increment by 1 do
          Sum ← Sum + N(i+u, j+v)
        end for
      end for
      Ave ← Sum / (15 * 15);
      for u= 1 → 15, increment by 1 do
        for v= 1 → 15, increment by 1 do
          if N(i+u, j+v) > Ave-8
            NI(i+u, j+v) ← 1
          Else NI(i+u, j+v) ← 0
          end if
        end for
      end for
    end for
  end for

  for i= 1 → W-1, increment by 1 do
    for j= 1 → H-1, increment by 1 do
      P1 ← NI(i-1, j-1);
      P2 ← NI(i-1, j);
      P3 ← NI(i-1, j+1);
      P4 ← NI(i, j-1);
      P5 ← NI(i, j+1);
      P6 ← NI(i+1, j-1);
      P7 ← NI(i+1, j);
      P8 ← NI(i+1, j+1);
      R1 ← P1+P4+P6+P3+P5+P8; //Equation (3.8)
      R2 ← P1+P2+P3+P6+P7+P8; // Equation (3.9)
      if (R1=0) OR (R2=0)
        B(i, j) ← 0; // set as black pixel
      end if
      if (R1+R2 >= 7)
        B(i, j) ← 255; // set as white pixel
      end if
    end for
  end for
End
    
```

Figure 7: Algorithm for Binarization process

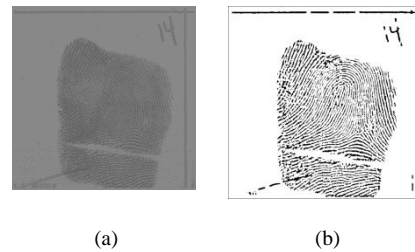


Figure 8: Binarization: (a) Normalized image; (b) Binarized image.

```

Input: Binarization Fingerprint Image B of size W X H.
Output: Skeleton Image SK.
\\ where Neighbors is an array of neighbouring pixels.
Begin:
  for i= 2 → W, increment-1 by 1 do
    for j=2 → H, increment-1 by 1 do
      Neighbors(1) ← B(i-1, j-1);
      Neighbors(2) ← B(i-1, j);
      Neighbors(3) ← B(i-1, j+1);
      Neighbors(4) ← B(i, j+1);
      Neighbors(5) ← B(i+1, j+1);
      Neighbors(6) ← B(i+1, j);
      Neighbors(7) ← B(i+1, j-1);
      Neighbors(8) ← B(i, j-1);
      D ← 0;
      for u= 1 → 8, increment by 1 do
        D ← D + Neighbors(u);
      end for
      TR ← 0;
      for u= 1 → 8, increment by 1 do
        F1 ← Neighbors(u);
        F2 ← Neighbors(u + 1 % 8);
        if (F1 = 0) & (F2 = 1)
          TR ← TR + 1;
        end if
      end for
      R1 ← Neighbors(2)*Neighbors(4)*Neighbors(6);
      R2 ← Neighbors(4)*Neighbors(6)*Neighbors(8);
      if D = 2 & D = 6 & TR=1 & R1=0 & R2=0
        B(i, j) ← 0
      end if
      R3 ← Neighbors(2)*Neighbors(4)*Neighbors(8);
      R4 ← Neighbors(2)*Neighbors(6)*Neighbors(8);
      if D = 3 & D = 6 & TR=1 & R3=0 & R4=0
        B(i, j) ← 0
      end if
      R5 ← Neighbors(1)*Neighbors(8)*Neighbors(6);
      R6 ← Neighbors(3)*Neighbors(4)*Neighbors(6);
      R7 ← Neighbors(5)*Neighbors(6)*Neighbors(8);
      R8 ← Neighbors(4)*Neighbors(6)*Neighbors(7);
      if (R5=1 & Neighbors(3)=0) ||
        (R6=1 & Neighbors(1)=0) ||
        (R7=1 & Neighbors(3)=0) ||
        (R8=1 & Neighbors(1)=0)
        B(i, j) ← 0
      end if
    end for
  end for
End.
    
```

Figure 9: Algorithm for Skeletonization process

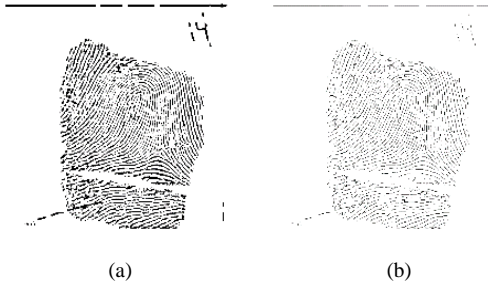


Figure 10: Skeletonization: (a) The input binarized image; (b) Skeleton image.

E. Proposed Image Fusion

Discrete Cosine Transform (DCT) is used to fuse between Histogram Equalized image and Skeleton image to produce an enhanced image with a clear ridge structure and an acceptable contrast. Firstly, both input fingerprint images are divided into non-overlapping blocks of 8×8 pixels.

The fusion process using DCT is based on the maximum information for each pixel block of both DCT images (Histogram Equalization (HE) and Skeletonization (SK)). The high information used in this study depended on the variance values of each block. In other words, the fusion process compared the variance values for each block, where the block with the highest value was included and the other ignored.

The algorithm as shown in Figure 11 summarizes the fusion process in pseudo-code form. The output of the fusion process was an enhanced greyscale image with clear ridge flow and high contrast as shown in Figure 12.

```

Input: Histogram Equalization Image HE; Skeletonization Image SK.
Output: Fused Image FU.
Begin:
for i = 1 → W, increment by 8 do
for j = 1 → H, increment by 8 do
for u = 0 → 7, increment by 1 do
for v = 0 → 7, increment by 1 do
im1Sub(u,v) ← HE(1+u, j+v);
im2Sub(u,v) ← SK(1+u, j+v);
end for
end for
im1SubDct ← dct(im1Sub);
im2SubDct ← dct(im2Sub);
for u = 0 → 7, increment by 1 do
for v = 0 → 7, increment by 1 do
im1Norm(u,v) ← im1SubDct(u,v) / 8;
im2Norm(u,v) ← im2SubDct(u,v) / 8;
end for
end for
im1Mean ← im1Norm(1,1);
im2Mean ← im2Norm(1,1);
S1 ← 0; S2 ← 0;
for u = 0 → 7, increment by 1 do
for v = 0 → 7, increment by 1 do
S1 ← S1 + im1Norm(u,v);
S2 ← S2 + im2Norm(u,v);
end for
end for
im1Var ← S1 - im1Mean;
im2Var ← S2 - im2Mean;
if im1Var > im2Var
for u = 0 → 7, increment by 1 do
for v = 0 → 7, increment by 1 do
dctVarFusion(u,v) ← im1SubDct(u,v);
end for
end for
Else
for u = 0 → 7, increment by 1 do
for v = 0 → 7, increment by 1 do
dctVarFusion(u,v) ← im2SubDct(u,v);
end for
end for
end if
imFusedSub ← idct(dctVarFusion);
for u = 0 → 7, increment by 1 do
for v = 0 → 7, increment by 1 do
FU(1+u, j+v) ← dctVarFusion(u,v);
end for
end for
end for
End
    
```

Figure 11: Algorithm for Fusion process



Figure 12: (a) Original image; (b) fused image (Source: NIST F0000008).

V. RESULT AND DISCUSSION

The performance of the current methodology is evaluated at every single methods in image enhancement presented here, using the standard practices which include both qualitative and quantitative measurements. Table 1 below depicts the above performance measures.

Table 1
Performance measures

Performance Measures	
Process	Fingerprint Enhancement
Qualitative	Visual inspection on image quality before and after enhancement.
Quantitative	Singular point Error rate.
Benchmarked with	Saparudin [9]

The quality of the ridge and valley in a fingerprint image is an essential characteristic, as these structures contain all the information associated with fingerprint features. Ideally, perfect images show alternating ridges and valleys that flow in locally constant direction. These are called high contrast images. This regularity in the fingerprint patterns facilitates the process of feature extraction. In the NIST 14 however, it is very rare to find images with perfect quality due to factors like skin variations, impression conditions and the illumination effect of capture devices. Due to these different types of noise that affect the clarity of fingerprint patterns, image enhancement techniques are often employed to reduce this noise effect and enhance the definition of ridges and valleys.

Combinations of enhancement techniques were applied to improve image quality and come up with an acceptable image contrast. The current method included five different enhancement techniques: Normalization, Histogram Equalization, Binarization, Skeletonization and Fusion. Each technique improved different aspects of the images' quality. The Normalization process standardized the pixel intensity which facilitated the processing of subsequent image enhancement stages. Subsequently, the Histogram Equalization technique increased the contrast of the images. Furthermore, the Binarization and Skeletonization techniques were implemented to differentiate between the ridge and valley structures and to obtain one pixel-wide lines. Finally, the Fusion technique was used to merge the results of the Histogram Equalization process with the Skeletonization process to obtain the new high contrast images.

The visual inspection was based on the comparison between the current enhancement technique and the latest study [9] where he relied only on Normalization and noise removal, while this current method also included actual image enhancement to improve image quality. In this chapter, fingerprint images are presented in the following order: The raw fingerprint image is on the left side, in the middle is the result obtained from Saparudin's [9] technique, and on the

right side is the result of the current technique. Figure 13 (a) through Figure 13 (e) shows a comparison between the two techniques using good quality images. There is no big difference between the results of the current method and the results of the existing techniques in good quality images in term of the differentiation between ridges and valleys, as well as the images' foreground and background. In good quality images, the effect of the Binarization and Skeletonization processes became clearly visible by increasing the contrast between the prints' ridges and valleys. Using the Binarization process a value of 0 was assigned to black pixels, representing the fingerprint ridges, and a value of 1 was assigned to white pixels, representing the valleys. The Skeletonization processes replaced more than one successive wide pixel by just one pixel wide line.

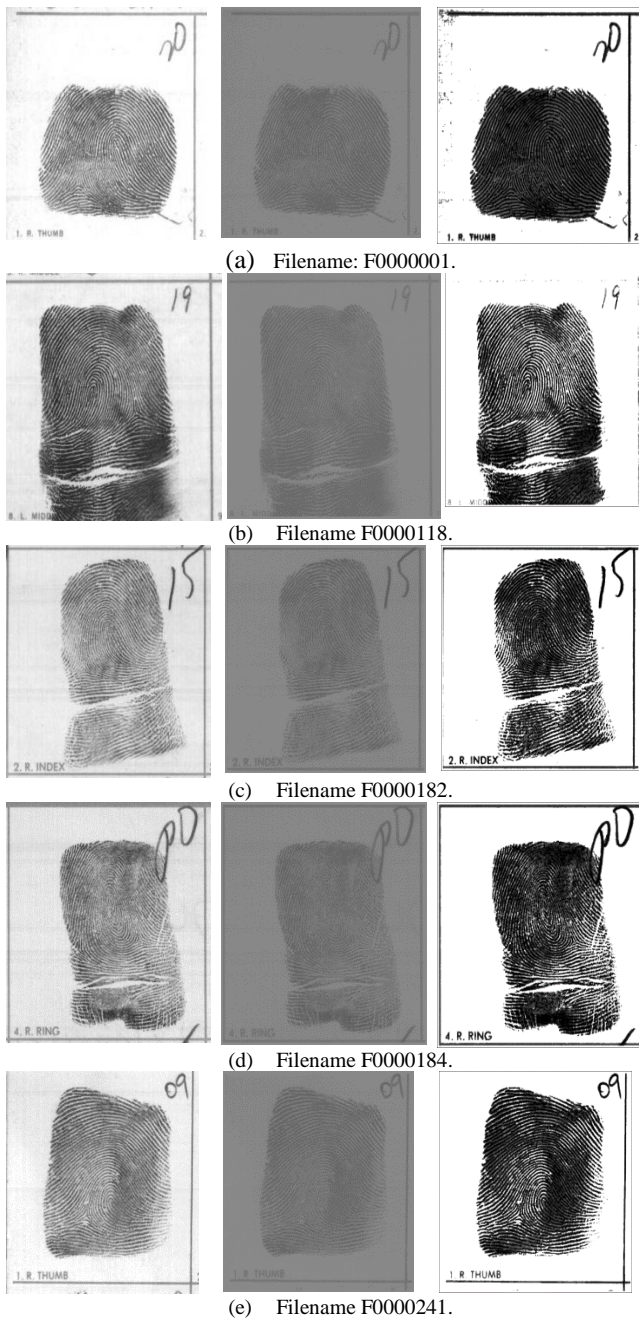


Figure 13: (a) to (e) are the comparison between the current enhancement technique and Saparudin's [9] technique using good quality image.

The quantitative evaluation of enhancement processes included the same criteria as was done in the research of Zhou

et al., [18] and Saparudin [9], which were based on the Miss rates and False alarm rates of singular points. For benchmarking purposes, the results of the current method were compared with the results of the studies conducted by Zhou et al., (2009) and Saparudin (2012). For this evaluation, a special experiment was conducted using 500 fingerprint images; file numbers F0000001 to F0000500, from the NIST 14. Results showed that the current method outperformed the two existing methods, both in terms of Miss Rate and False alarm rate of singular point identification. Looking at the Miss rate for Core and Delta points, the current method showed positive results, particularly for the Delta points. The current method detected all the Delta points that were located along image borders, while the two existing methods did not. A summary of the Miss Rate results for Core and Delta points is presented in Table 2.

Table 2
Summary of Miss rates for Core and Delta points

Methods	Zhou [18]	Saparudin [9]	Current method
TNS	665	665	665
NMC	33	34	28
PMC	4.96	4.81	4.21
NMD	63	109	34
PMD	9.47	16.39	5.11

TNS: Total Number of Singularities (Core and Delta points).
 NMC: Number of Miss Rates of cores (i.e. discarded true cores).
 PMC: Percentage of Miss Rates of cores.
 NMD: Number of Miss Rates of deltas (i.e. discarded true deltas).
 PMD: Percentage of Miss Rates of deltas.

The False alarm rate of the Core and Delta points using the current method is more performant than the ones used by Saparudin [9] and Zhou [18]. A summary of the False alarm rate of the Core and Delta points for the three methods is given in Table 3. Figure 14 shows a visual comparison of all three methods

Table 3
Summary of False alarm rate for Core and Delta points

Methods	Zhou [18]	Saparudin [9]	Current method
TNS	665	665	665
NFC	182	39	31
PFC	27.37	5.86	5.11
NFD	139	14	12
PFD	20.90	2.11	1.8

TNS: Total Number of Singularities (Core and Delta).
 NFC: Number of False Alarm Rate of Cores (i.e. discarded true cores).
 PFC: Percentage of False Alarm Rate of Cores.
 NFD: Number of False Alarm Rate of Deltas (i.e. discarded true deltas).
 PFD: Percentage of False Alarm Rate of Deltas

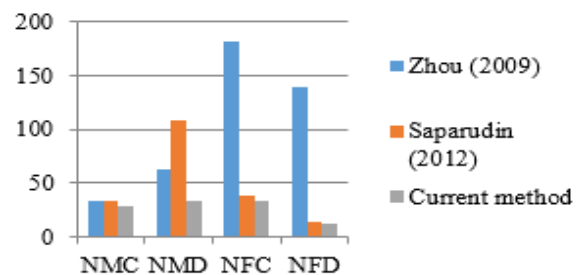


Figure 14: Summarized results of the Quantitative Evaluation of the current method in term of Miss Rate and False alarm rate of singular points

VI. CONCLUSION

In the Enhancement process, different techniques were used to improve image quality by first normalizing the image. Histogram Equalization was applied on the normalized image to increase the image contrast. Then, Binarization process converted the image into binary form, followed by the Skeletonization process to get one pixel-wide lines. Finally, the Histogram Equalized image and the skeleton were fused using Discrete Cosine Transform (DCT) that finally yielded an enhanced fingerprint image.

As a new contribution for this study, a new fingerprint image enhancement technique is developed by improving the image contrast via Histogram Equalization process. The problem of disconnectivity in the fingerprint patterns is eliminated using Skeletonization process. The advantages from both the processes are combined by applying fusion technique using DCT to acquire enhanced image.

This work continues, exploring the more pertinent and realistic research problem of automatic fingerprint classification. These will include: fingerprint segmentation process, established new orientation fields estimation method, detecting the singular point in a fingerprint image, correctly estimated the rotation of the symmetric axis, extracted valid features and fully automatic fingerprint classification.

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