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Impact of Noisy Singular Point Detection on Performance of Fingerprint Matching

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Abstract—The performance of fingerprint matching has significantly improved in the recent times. However, this performance is still affected by many factors such as inadequate detection of singular points, poor-quality and noisy fingerprint images mostly result in spurious or missing singular points, which generally results in degradation of the overall performance of the fingerprint matching. This paper presents the impact of noisy or spurious singular (core/delta) points on the performance of fingerprint matching. The algorithm comprises of image enhancement stage, the singular points extraction stage and post-processing stage. The image enhancement stage preprocessed the fingerprint images, the singular point extraction stage extracts the true and the noisy or false singular points, while the post processing stage eliminate the spurious singular point. Benchmarked FVC2000, FVC2002, FVC2004 and FVC2006 fingerprint databases which comprise four datasets each were used for the experimental study. The completion time for the singular point extraction on each dataset were computed. The matching algorithm was also implemented to verify the impact of noisy singular points on false non match rate (FNMR), false match rate (FMR) and matching speed. The completion time extraction of singular points from the noisy fingerprint images is 263seconds whereas the completion time for extraction of true singular points is 82seconds. The increase in completion time is due to the inclusion of spurious features (noise/contaminants), whereas there is time decreases after the spurious features had been eliminated. The obtained values and analysis revealed that poor and noisy quality fingerprint images have adverse effect on the performance of fingerprint matching.

Keywords — Experimental Study, Singular Point, Core and Delta, Fingerprint Matching.

1. Introduction

Fingerprint have been widely used in automated fingerprint identification systems (AFIS). The fingerprint features comprise of the ridges and valleys patterns of a finger. The ridges are the dark and raised layers while the valleys are the white and lowered portions (Zhou, et. al., 2009; Bazen and Gerez, 2001, Iwasokun and Akinyokun 2014). Fingerprint acquisition usually begins with enrolment of the fingerprint image. The acquired fingerprint images undergo enhancement stages which include, image segmentation, normalization, filtering, Binarization and thinning (Jeyalakshmi and Kathirvalavakumar, 2017).

Fingerprint enhancement can be conducted on either binary images or grey level images. In binary image, the ridge pixels are assigned value zero while value one is assigned to valley pixels. When the ridge extraction algorithm is applied on grey images, information about the true ridge structure is often lost depending on the performance of the ridge algorithm, hence there is need for an enhancement algorithm to improve the quality of ridge structure (Naja and Rajesh, 2015). Most fingerprint matching systems rely on minutiae and singular points features. The process of obtaining the point of alignment between two sets of minutiae during fingerprint matching is a difficult task and most minutiae based algorithm are time consuming and complexity. These constraints can be reduced or overcome by using fingerprint singular points (Chikkerur and Ratha, 2007).

Singular points, which is the most prominent among global features, contains the significant global information required for fingerprint pattern classification and serves as reference points in most fingerprint pattern algorithm (Chen, et. al., 2019).

Commonly used singular points are the core and delta points (also referred to as singular points or singularities) At core point, the ridge experiences maximum turning (change in orientation) while it experiences a tri-dimensional change at the delta point as shown in Figure1(Ogunlana, 2021; Ogunlana, et. al., 2021; Iwasokun and Akinyokun, 2014; Iwasokun, et. al., 2014). These points are highly stable and are also rotation and scale invariant. Thus, it is widely used by most classification methods.

Singular points are important because they determine the topological structure of the fingerprint and its class.

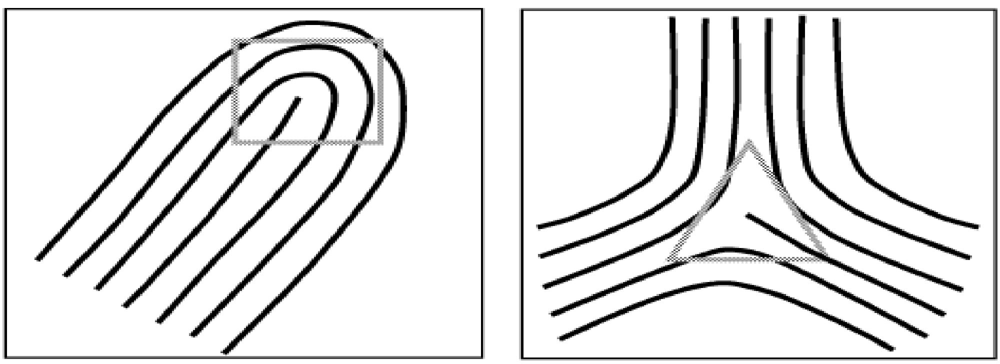


Figure 1: The Singular Points on a Fingerprint Image

Singular points (SPs), formed the basic features used for fingerprint matching, indexing, classification, arrangement and orientation field modeling (Iwasokun, 2015). There already existing many singular point detection algorithms, most of them can effectively detect the singular point when the image is of good quality, however, not much emphasis has been placed on the detection of singular points on noisy or spurious fingerprint images as shown in Figure 2.

The detection of singular points is still confronting challenges due to the following (Ogunlana, 2021; Johal and Kamra, 2011).

1. Poor quality of fingerprint image
2. Presence of noise or artefacts or contaminants introduced by sensors during enrolment.
3. Fingerprint with only partial image
4. The presence of scar, break, too oily, too dry and so on.

Several approaches have been proffered by different authors for the detection of singular points which include Poincare Index method (Zhou, et. al..2009; Ogunlana, 2021; Iwasokun and Akinyokun, 2014; Bo, et. al., 2008), Fault-Tolerant (Saquib, et. al., 2011), Directional Field Estimation (Bazen and Gerez, 2001), Orientation field (Jeyalakshmi and Kathirvalavakumar, 2017; Alhalabi, et. al., 2019; Kharat and Khodwe, 2012; Khalil, et.al., 2010; Chaudhari et.al., 2012, Kumar et. al., 2012, Johal and Kamra, 2011), Euclidean distance (Bhargava, et. al., 2015). Others are Entropy-based clustering (Le, et. al., 2019), Faster Region-based Convolutional Network (Faster-RCNN) (Liu, et. al., 2018), Convolutional Neural Network (Chen et. al., 2020), Ridge Orientation Map (Bahgat, et. al., 2013), Gradients Field Mask (Mishra and Shandilya, 2010), Multi-Resolution (Zhang and Wang, 2002). This paper contributed to knowledge by developing a matching algorithm that perform well on the noisy fingerprint images. The results revealed that poor and noisy fingerprint images had adverse effect on the performance of the fingerprint matching and must be eliminated as much as possible in order to get a desirable result. The rest of this paper is organized as follows. Section 2 of the paper presents the review of some of the existing works in compliance with research paper as detailed in Misra (2021), while Section 3 discusses the fingerprint singular points extraction technique. Sections 4 and 5 present the experimental study and the conclusion drawn respectively.

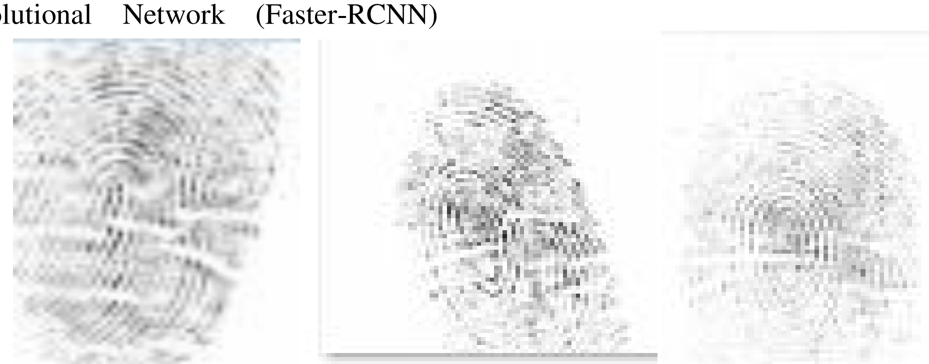


Figure 2: Noisy and poor quality fingerprint images (www.bias.csr.uibo.it/fvc2000/download.asp)

2. Some Existing Works

Many approaches have been proposed for fingerprint singular points detection with their strengths and weakness. The authors in (Zhou, et. al., 2009) developed an algorithm for detecting singular point from fingerprint images using Poincare index method and an algorithm called DORIS was used to remove the spurious singular points. Though, the approach is susceptible to forged detection, the result showed the accuracy and robustness of the algorithm. The authors in (Bazen and Gerez, 2001) proposed an algorithm for extracting singular points using high resolution directional fields of fingerprints. The core and delta points as well as orientation of the fingerprint were detected. The finding is used for accurate alignment of two fingerprints in a fingerprint verification system but the algorithm fails with low degraded and noisy images. The authors in (Jeyalakshmi and Kathirvalavakumar, 2017) proposed an algorithm that estimate orientation image using Multi-scale principal component analysis (PCA), and used shape analysis to detect the true singular points locations. The use of rules based on location of singular points orientation information below upper core point was applied. The algorithm performed effectively with ambiguous and spurious fingerprint images, but only classifies images into its primary and secondary class only.

A method for reliable detection of singular points which is largely insensitive to the degradation of fingerprint quality is proposed in (Saquib, et. at., 2011). The detection of the singular points which operates on information based on quadrant change was first carried out followed by the extraction of singular points using orientation reliability measure of the filtered fingerprint image. The approach was effective in eliminating the spurious singular points in the noisy images. However, the algorithm is computationally expensive.

A cluster-based computational approach for reliable orientation field estimation based on a directional filter bank framework is proposed in (Alhalabi, et. al., 2019). A Coherence-Enhancing Diffusion (CED) was used to improve the fingerprint quality before feature extraction process. The estimation orientation field then serves as input data for the CED engine for further enhancement of the noisy fingerprints for a better recognition performance. The algorithm produced accurate orientation results. However, orientation fields cannot achieve reliable and accurate detection of poor quality fingerprints. Also, the algorithm has a high computational complexity.

The authors in (Chen, et. al., 2019) proposed an algorithm for singular point detection based on low-resolution image processing technique and Poincare Index method. 2D discrete wavelet transform (DWT) was used to conduct the fingerprint image operation. Then, a LL-band image that has ¼ resolution of the original image was obtained to reduce the operation needed for subsequent operations. False singular points were removed by computing the local binary patterns (LBP) as a reference for selecting correct singular points. Although, the algorithm was able to reduce the chance of detecting false singular points, the algorithm required a long processing speed for its operations.

Chikkerur and Ratha (2005) presented an algorithm to evaluate the impact of singular point detection on fingerprint performance. The authors algorithm was based on the use of complex filtering method to extract core and delta locations with precision, and a modified graph based marching algorithm to run in linear time in the presence of core and delta points. The experimental evaluation was carried out using benchmarked FVC2002 database consisting of 800 images made up of 100 individuals with 8 print each. The proposed algorithm showed significant improvement in average verification time and accuracy when reliable core and delta point are used. However, the algorithm may perform badly with poor and noisy quality fingerprint images.

Kamar, et.al., 2012 proposed a novel algorithm for detecting singular points using reliability of the fingerprint orientation field. After the completion of the enhancement stages, the algorithm was evaluated on benchmarked FVC2002 database using detection rate, percentage of false singular point and percentage of missed singular points as standard metrics. Although, the algorithm performs well with high detection rate, however, the algorithm cannot locate the particular singular points in a fingerprint image.

A new method of detection and localization of core point in a fingerprint is proposed in Johal and Kamra (2011). The method applied is based on the enhanced fingerprint image orientation reliability. The algorithm was experimentally tested using 180 fingerprints from different fingers. The proposed algorithm gave a near accurate results for noisy images, but failed with an extreme poor quality images.

Chen et. al., (2020) proposed a new customized convolutional neural network called SinNet for the fingerprint singular point detection. A simple and fast post-processing approach also used to locate the singular points. The training data labeling, the mixed loss function, the encoder-decoder architecture, the inception model, skip connection and the batch normalization were used to ensure the efficient performance of the network. The performance evaluation was conducted using the publicly singular point detection competition 2010 (SPD2010) datasets. A simpler, better and accurate algorithm for extracting singular point was developed. However, the algorithm failed with noisy and spurious images.

Summary of the existing works is further presented in Table 1.

Table 1: Summary of some existing works on fingerprint singular point detection

Research	Methodology	Strength	Weakness
Zhou, et. al., (2009)	Poincare Index method and DORIS	Accurate and robustness	Susceptible to forge detection
Bazen and Gerez (2001)	High resolution directional field	Accurate detection of singular point alignment	Perform poorly with noisy images
Jeyalakshmi and Kathirvalavakumar (2017)	Multi-scale principal component analysis (PCA)	Perform effectively with spurious fingerprint images	assified images into primary and secondary only
Saquib, et. at., (2011)	Orientation reliability approach	Effective performance with noisy image	Computationally expensive
Alhalabi, et. al., (2019)	Coherence-enhancing diffusion	High level of accuracy	Failed with poor quality images
Chen, et. al., (2019)	Poincare index method and 2D discrete wavelet transform (DWT)	Accurate in false singular point detection.	Algorithm cumbersome with long processing execution speed.
Chikkerur and	Complex filtering and	High verification	Perform poorly with noisy

Ratha (2005)	modified graph based method	time and accuracy	fingerprint images
Kamar et al., (2012)	Orientation field	High detection rate	Unable to locate fingerprint singular point
Johal NK and Kamra A (2011)	Orientation reliability approach	Low accurate result with noisy images	Failed with extreme poor quality images.
Chen et. al., (2020)	Convolutional neural network	Simpler and accurate extraction of singular point	Failed with spurious images.

3. Fingerprint Singular Point Extraction Technique

The process of fingerprint image enhancement and singular point extraction is depicted in Figure 3.

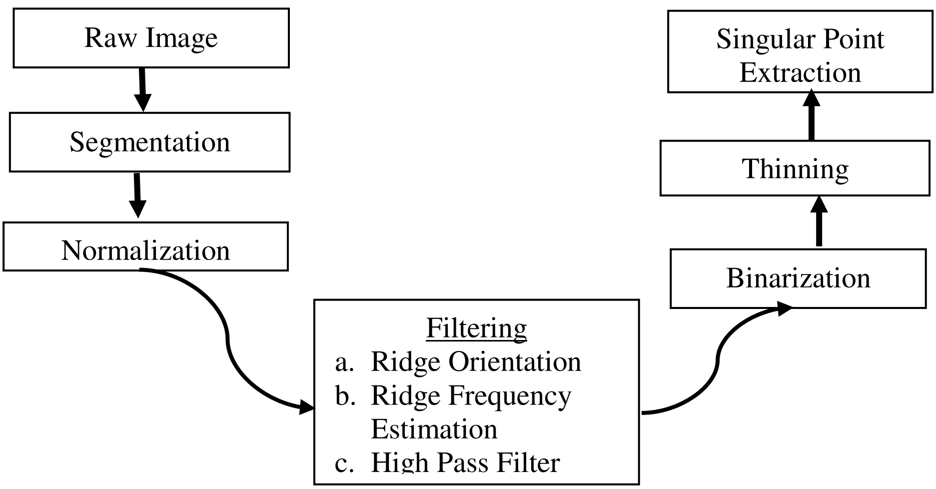


Figure 3: Algorithm for Fingerprint Singular Point Detection

3.1 Image Enhancement

The fingerprint image enhancement process begins with image segmentation. The clear pattern area containing the ridges and valleys which is the regions of interest (ROI) are separated from the background corresponds to the regions outside the borders of the fingerprint area which contains noise and contaminants. The background region usually exhibits a very low grey-scale variance while the foreground region has a high variance. This necessitates the use of method base on variance thresholding for segmentation. Segmentation involves sub-division of image into blocks of βxβ and the grey-level variance of each block is computed from (Iwasokun, et. al., 2014):

$$\alpha(k) = \beta^{-2} \sum_{i=1}^{\beta} \sum_{j=1}^{\beta} (\varphi(i,j) - \gamma(k))^2 \quad \ldots \qquad (1)$$

$$\gamma(k) = \beta^{-2} \sum_{a=1}^{\beta} \sum_{b=1}^{\beta} \tau(a,b)$$

Where $\alpha($ k$)$ is the variance for block k, $\varphi(i,j)$ and $\tau(a,b)$ are the grey-level value at pixel (i,j) and (a,b) respectively in block k, $\gamma(k)$ is the mean grey-level value for block k.

The segmented image undergoes normalization in order to standardize the image intensity value by adjusting the range of a grey-level value to lie within a desired range of values. The normalized image is defined as follows (Iwasokun, et. al., 2014; Iwasokun, 2015):

$$\omega(i,j) = \begin{cases} \delta_0\sqrt{\frac{\sigma_o(\varphi(i,j)-\delta)^2}{\sigma}} \ if \varphi(i,j) > \gamma \\ \delta_0\sqrt{\frac{\sigma_o(\varphi(i,j)-\delta)^2}{\sigma}} \ otherwise \end{cases} \quad \ldots(2)$$

Where $\varphi(i,j)$, ω(i,j), δ and σ are the grey-level value, the normalized grey-level value, the estimated mean and variance at pixel (i,j) respectively. δ_o, $\sigma_o$are the desired mean and variance after the normalization respectively.

Filter is necessary to further improve the depurated fingerprint image by removing noise and preserving the true ridge and valley structures. This stage involves the basic process of orientation estimate and ridge frequency estimate.

The local orientation for each block centered at pixel (i,j) is computed as follows (Chen, et. al., 2019):

$$V_x(\mathrm{i,j}) = \sum_{u=i-\frac{w}{2}}^{i+\frac{w}{2}} \sum_{v=j-\frac{w}{2}}^{j+\frac{w}{2}} 2\partial_x(u,v)\partial_y(u,v) \ldots \quad (3)$$

$$V_y(\mathrm{i,j}) = \sum_{u=i-\frac{w}{2}}^{i+\frac{w}{2}} \sum_{v=j-\frac{w}{2}}^{j+\frac{w}{2}} \partial_x^2(\mathrm{u,v})\partial_y^2(\mathrm{u,v}) \ \ldots \quad (4)$$

$$\theta(i,j) = 0.5tan^{-1}\frac{v_y(i,j)}{v_x(i,j)} \quad \ldots \quad (5)$$

Where w is the size of the local window, $\partial_x(u,v)$ and $\partial_y(u,v)$ represents gradient magnitudes at each pixel in x and y directions respectively, $\theta(i,j)$ is the least square estimate of the local orientation of the block centered at pixel (i,j).

The application of Gabor filter on the images is as follows:

$$G(x,y,f,\theta) = exp\left\{\frac{1}{2}\left[\frac{a^2}{\delta_x^2} + \frac{b^2}{\delta_y^2}\right]\right\}\cos(2\pi fa \quad \ldots \ (6)$$

$$a = xsin\Theta \ + ycos\Theta \quad \ldots \quad (7)$$

$$b = \ xcos\Theta \ + ysin\Theta \quad \ldots \quad (8)$$

Where f is the frequency of the cosine wave along the direction θ from the x-axis, and $\delta_x$and δ_y are the space constant along x and y axes respectively.

The image obtained from the application of the Gabor filter is binarized and subsequently thinned to obtain its best and optimal performance threshold. The optimal is the one that maximizes the between-class variance and the one that minimizes the within-class variance.

3.2 Singular Point Extraction

The extraction of singular point from the thinned image is based on a Modified Poincare Index method as follows (Ogunlana, 2021; Iwasokun and Akinyokun 2014; Chen, et. at., 2019):

$$S(m,n) = \frac{1}{\pi}\sum_{c=1}^{2}\sigma_c \cdots \ (9)$$

$$\sigma_c = \begin{cases} p(c)+\pi\ ; \ \ p(c) \le -\frac{\pi}{2} \\ \ \ p(c)\ ; \ \ p(c) > -\frac{\pi}{2} \\ p(c)-\pi; \ \ otherwise \end{cases} \quad \ldots \ (10)$$

$$p(c) = |\cup_{c+1} - \cup_c|, \ \cup_9 = \cup_1 \quad \ldots \ (11)$$

Where PC(i,j) represents singular point characteristics, (i, j) are orientation direction, σ_c is the computed point characteristic, $\cup_1, \cup_2, \ldots, \cup_8$ represents the orientation of the 3x3 neighbors of pixel (i,j). Based on these characteristics, the core point lies between -1 and $-{}^{1}/_{2}$ for PC(i,j) while the delta point is in the range ${}^{1}/_{2}$ and -1.

3.3 Post-Processing Stage

The post-processing stage commenced by eliminating the noticeable false core and delta points using a 2-step algorithm as follows (Ogunlana, 2021; Iwasokun and Akinyokun 2014):

1. The **average** core (or delta) is calculated if there is more than one core (or delta) in a circular region with radius of 8 pixels. Given that μ cores (or delta) exist in an area, $\{(\omega_i, \rho_i), \ i=1, 2,3,\ldots,\mu)\}$ then, average core (or delta) (ω, ρ) is computed from:

   $$\omega = \mu^{-1} \sum_{i=1}^{\mu} \omega_i \quad \ldots \quad (12)$$

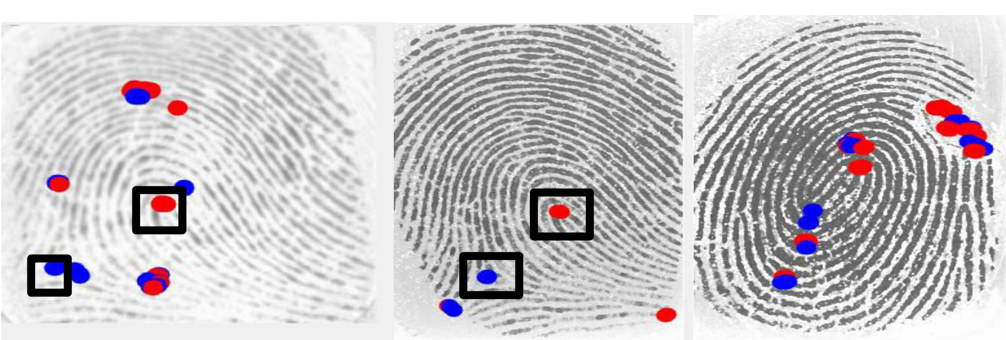
   $$\rho = \mu^{-1} \sum_{i=1}^{\mu} \rho_i \quad \ldots \quad (13)$$

2. Eliminate both core and delta points if the distance between them is less than or equal to 8 pixels apart.

4. Experimental Study

The experimental study was carried out in a Microsoft Windows 10 Professional platform on HP Pavilion Core i7 8.00GB RAM 750 GB HDD using Matrix Laboratory (Matlab) R2018a. Benchmarked FVC2000, FVC2002, FVC2004 and FVC2006 fingerprint databases served as experimental datasets. Each of the database comprises of four datasets DB1, DB2, DB3 and DB4 and was jointly produced by the Biometric Systems Laboratory, Bologna, Pattern recognition and Image Processing Laboratory, Michigan and the Biometric Test Center, San Jose, United States of America. Images in the four datasets were enrolled using low-cost capacitive fingerprint reader from multiple sources and of varied quality. Each of the dataset has eighty (80) fingerprints of varied qualities.

The result of the fingerprint image without enhancement produced true and false core and delta points as shown in Figures 4(a-c). The true and the false core points are shown with red color while the true and the false delta points are denoted with blue color. For good quality images, all the algorithms effectively located the core and delta points. With average quality images, the algorithms extracted few false core and delta points, while the higher number of extracted false core and delta points occurred in noisy and poor images. This is as a result of noticeable cases of noise regions in several of the images with great number of artifacts and contaminants. There is need for the fingerprint images to undergo enhancement stages so as to reduce or eradicate all the noise that may generate false core and delta points. The results of the noisy fingerprint images in Figures 5(a-c) which undergo various enhancement stages are shown in Figures 5(d-f). The figures 5(d-f) presented the extracted singular (core and delta) points of the images based on the Algorithm in [6-8].



(a) (b) (c)

Figure 4: Fingerprint Images and their extracted true and false core points without enhancement process

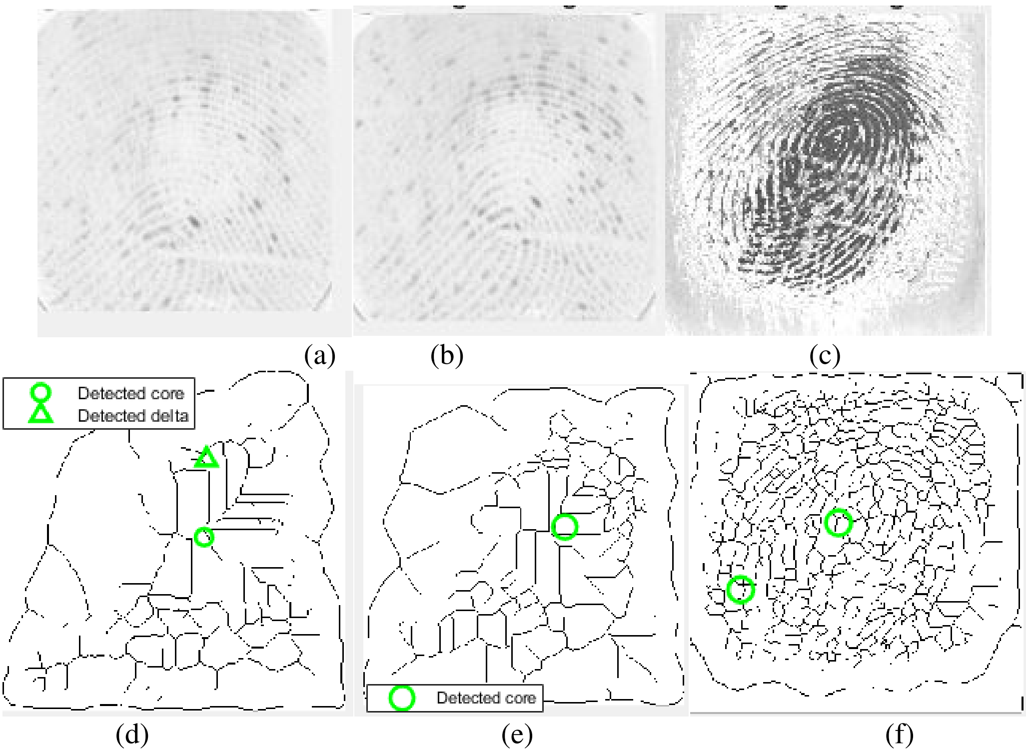


Figure 5: Noisy Fingerprint Images and their extracted true and false core points after enhancement processes

The results from the singular points extraction experiments for the noisy images on the four benchmarked fingerprint databases using the Modified Poincare Index algorithm are presented in Table 2. It was shown that there is increase in completion time taken for extraction process of the noisy fingerprint images. In good quality images, the algorithms are saved from the difficulty of extracting false singular points resulting in fewer computations and consequently, lesser computation time while the tendency of false extraction and several computations increase as the quality of the images decreases.

The results of post processing stage which eliminated all the false core and delta points from the images in the four databases as shown in Figure 6(a-c) and the extracted core and delta points as shown in Figure 6(d-f) are presented in Table 3. There is a significant reduction in the completion time when compared with Table 2. Poor and spurious features have the effect of increasing the completion time, whereas the completion time decreases in case of true singular point detection. The increase in completion time is most significant when both reference and template fingerprint images are of poor quality.

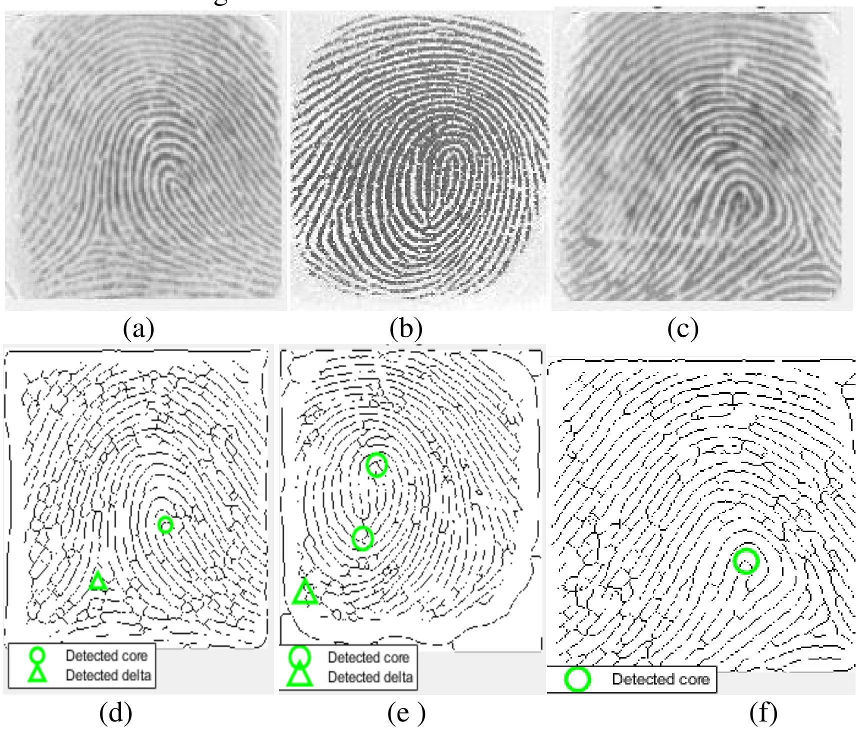


Figure 6: Enhanced fingerprint Images and their true extracted core points

Table 2: Result of extracted singular points from noisy fingerprint images from four databases

Dataset		FVC2000		FVC2002		FVC2004		FVC2006	
		Total	Time(s)	Total	Time(s)	Total	Time(s)	Total	Time(s)
DB1	Core point	24	163.88	39	254.1	35	276.1	40	263.52
	Delta point	10		16		20		40	
DB2	Core point	43	400.06	13	115.5	34	251	42	354.24
	Delta point	40		12		16		40	
DB3	Core point	40	347.04	40	231	32	266.06	38	302.4
	Delta point	32		10		21		32	
DB4	Core	37	216.9	48	406.56	24	200.8	35	280.8

	point								
	Delta point	8		40		16		30	

Table 3: Result of extracted singular points based on post-processing algorithm for four databases

Dataset		FVC2000		FVC2002		FVC2004		FVC2006	
		Total	Time(s)	Total	Time(s)	Total	Time(s)	Total	Time(s)
DB1	Core point	56	134.62	41	62.32	45	55.18	40	82.4
	Delta point	50		41		44		40	
DB2	Core point	37	92.71	67	98.04	46	53.32	38	76.22
	Delta point	36		62		40		36	
DB3	Core point	32	81.28	30	45.6	48	64.48	42	86.52
	Delta point	32		30		56		42	
DB4	Core point	35	82.55	32	47.12	24	29.76	45	91.67
	Delta point	30		32		24		44	

Based on a fingerprint matching, false match rate and false non-match rate experiment were performed on the four databases for the impact of noisy singular points on performance of fingerprint matching.

Table 4: Completion Time(s) for Noisy Core Point Fingerprint Matching

Dataset	FVC2000		FVC2002		FVC2004		FVC2006	
	FMR	FNMR	FMR	FNMR	FMR	FNMR	FMR	FNMR
DB1	10.55	12.42	9.66	11.38	10.32	12.46	10.55	11.99
DB2	09.28	10.78	10.24	10.44	10.72	11.91	11.62	11.02
DB3	11.38	11.23	10.73	10.29	11,09	10.42	10.45	12.01
DB4	10.22	10.51	11.59	11.19	12.17	11.07	10.77	10.75

Table 5: Completion Time(s) for the True Core Point Fingerprint Matching

Dataset	FVC2000		FVC2002		FVC2004		FVC2006	
	FMR	FNMR	FMR	FNMR	FMR	FNMR	FMR	FNMR
DB1	0,10	3.84	0.12	2.01	0.14	3.72	0.05	1.88

DB2	0.12	2.51	0.15	3.07	0.07	1.99	0.15	3.22
DB3	0.15	1.76	0.14	2.22	0.12	1.84	0.22	2.33
DB4	0.11	3.44	.0.12	1.58	0.14	2.45	0.15	3.05

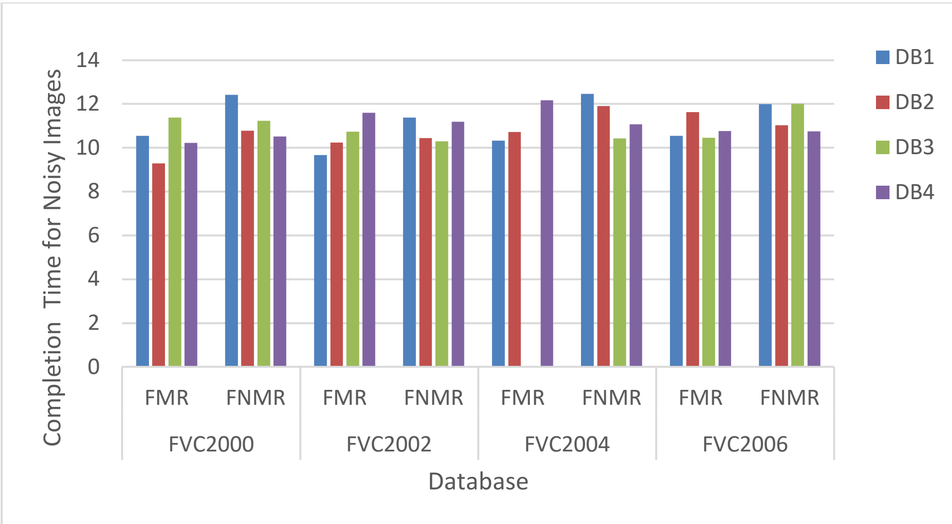


Figure 7: Completion Time of the FMR and FNMR values for Noisy core points for all datasets

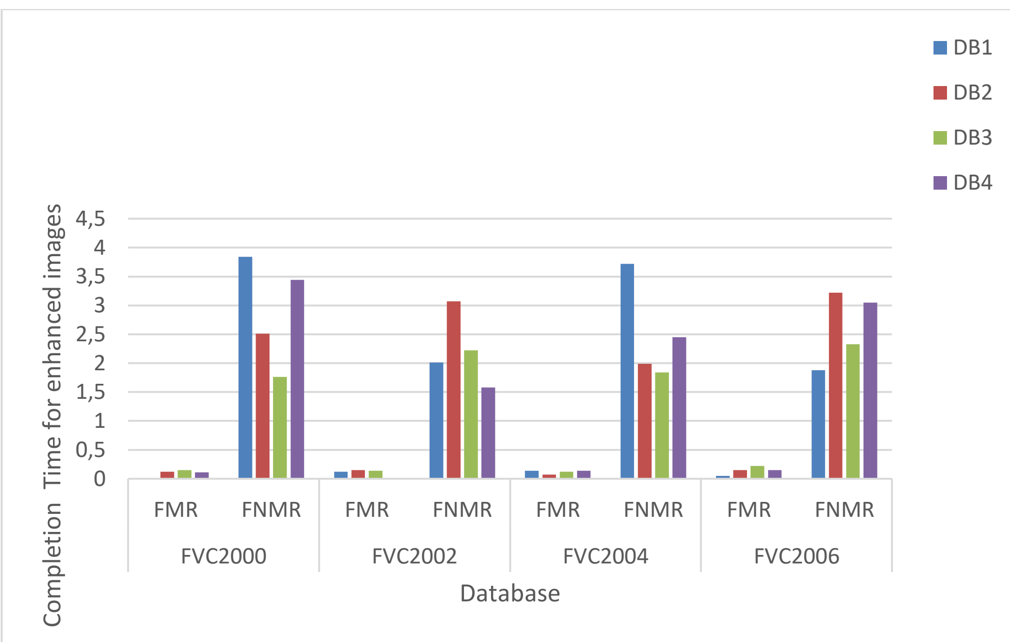


Figure 8: Completion Time of the FMR and FNMR values for True core points for all datasets

The completion time (in seconds) for FMR and FNMR experiments on the 80 fingerprint images in each of the datasets for each of the benchmarked database are shown in Tables 4 and 5. There is increase in Completion time in Table 4 due to inclusion of false and contaminants in the fingerprint images. The high error rates for matching in Table 4 indicated that the presence of the noisy singular points adversely affect the performance of a fingerprint matching algorithms. As image quality worsen, more missed or spurious feature points are generated resulting in a greater number of missed and spurious matching. Figures 7 and 8 clearly show a wide variation between the computation time for FMR and FNMR in Modified Poincare Index and post-processing experiments. It was observed that there is decrease in completion time for post processing experiment in Table 5. This was as a result of fewer number of singular points search and minimum computation. It is revealed that the matching based on true singular points produced lower error rates for all the databases. The experimental results show that this approach has significant impact on the accuracy and detection of noisy images and low contrast images. Only benchmarked fingerprint databases were used in this work. Future work will incorporate the locally enrolled fingerprint database.

5. Conclusion

This paper presented the experimental study of the impact of noisy and spurious singular points on the fingerprint matching. The first phase of the experiment was extraction of fingerprint singular (core and delta) points from noisy or degraded images without undergoing enhancement processes, while, the second phase of the experiment was the extraction of singular points after enhancement processes. Analysis of experimental results for both feature extraction and post-processing algorithm on FVC2000, FVC2002, FVC2004 and FVC2006 benchmarked fingerprint databases were carried out. It was revealed that, for noisy and spurious fingerprint images, there is tendency for poor enhancement, as well as extraction of false or multiple singular points which will definitely lead to inaccurate matching results.

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