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Utility of Quality Metrics in Partial Fingerprint Recognition

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Abstract: The performance of a fingerprint recognition system depends on the amount of discriminating data available in a fingerprint. The partial fingerprints do not contain enough details for successful matching. Partial fingerprints does not only degrades the matching performance but also introduces a security flaw in an authentication system. The probability of attacking many users with the help of dictionary attack is much higher when the fingerprints are partial. For reliable fingerprint matching and reducing the security flaw, it is necessary to check whether the fingerprint is partial or not. Fingerprint Quality metric plays an important role in assigning quality value to each fingerprint according to the content available in it. Depending on the quality value, the recognition system needs to take the decision on whether to allow, enhance, or re-acquire the fingerprint image. The paper assesses the ability of a fingerprint image quality metric to detect partial fingerprints as low-quality fingerprints. Extensive evaluation of the ten fingerprint image quality methods is performed to check their performance on partial fingerprints in terms of Utility. A new partial fingerprint dataset is prepared by cropping the fingerprints in FVC 2004 DB1A dataset to check the ability of quality metrics in handling the partial fingerprints. To calculate the match scores, two minutia-based matchers, NIST-Bozorth3 and K-Plet are used. The experimental results in this research shows that NFIQ 2.0 and Gabor based method are good at detecting partial fingerprints by assigning them low quality values.

Keywords: Partial Fingerprint, Image Quality, NFIQ, Gabor, Biometrics, Utility.

1. INTRODUCTION

Recent technological advancements have made the processing power and hardware faster, smaller and cheaper. Due to this, biometric recognition systems are being widely adopted at various places all over the world [1]. Among all the biometric recognition systems, fingerprint recognition have proved it's mettle in forensic applications as well as various access and border control systems [2]. Everyone is using fingerprint authentication in one way or other. To unlock the smartphones and proving ones identity at various places, biometric authentication is needed. Recently, Unique Identification Authority of India (UIDAI) have successfully completed the process of acquiring Biometric information of all its citizens [3]. This is one of the largest collection of biometric information consisting of Fingerprints, Iris and Face data. With the help of this, they have assigned the Unique Identification number (UID) to every citizen of the country. This has resulted in savings of billions of government money by removing fake beneficiaries and ensuring that subsidies reach the targeted audience by using direct benefit transfer [4].

The performance of a biometric recognition system depends heavily on the quality of an input fingerprint image [5,6,7]. The age and occupation of the person, fingerprint pressure on sensor, temperature and moisture level etc., affects the quality of the fingerprint image. For successful matching, it is very important to extract fingerprint features like minutia, singular points, ridge orientations etc. It is difficult to extract these features from poor quality fingerprints. Fingerprint image quality module plays an important role of checking the quality of the acquired input fingerprint image. Figure (1), depicts the role of quality check module in the overall fingerprint recognition system. Fingerprint acquisition module acquires the fingerprint image of the user, according to the specifications of the sensor. Fingerprint enhancement module tries to enhance the acquired image by repairing broken ridges and reducing the noise. Quality check module checks whether the input fingerprint image is suitable for matching or not. The quality check module assigns the quality score to fingerprint image denoting good or poor quality. If the image is of good quality then the image is passed to the feature extraction and matching module. If the fingerprint is of poor quality then it has to be re-acquired.

Another problem that affects the performance of the recognition system is the partial fingerprints. Main reasons

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behind the generation of the partial fingerprints are non-cooperation from a user, improper fingerprint placement on a sensor and miniaturization of fingerprint acquiring sensors. The average size of a fingerprint is 0.5" × 0.7", sensors having an area less than this size captures only partial fingerprints [8]. As partial fingerprint does not contain enough discriminating features, there is a high chance of it getting matched with some part of the impostor's whole fingerprint.

Most of the partial fingerprint recognition methods tries to improve the recognition performance by employing extra features, as partial fingerprints does not have enough discriminating features. Unfortunately, performance improvement in partial fingerprint recognition methods introduces security flaw in the system. It increases chances of partial fingerprints matching with many impostor fingerprints. It is very important to identify partial fingerprints and ensure that it will not reach the matching stage. The fingerprint quality metric has crucial role to play in assigning low quality values to partial fingerprints, so that further modules in the fingerprint recognition system can take appropriate action. The best way is to detect partial fingerprints at early stages of the fingerprint recognition system. Now the onus is on the fingerprint image quality methods to detect partial fingerprints at an early stage by assigning them low quality value. Appearance and subjective features are not of much importance while calculating the fingerprint image quality. Ultimately, what matters is the matching performance, means the good quality fingerprint should give high match score at matching stage. Grother and Tabassi first proposed this idea for performance measurement of a quality metric [9]. Separation between the genuine and impostor score distributions are used, as the measure of quality metric's performance. Higher separation between genuine and impostor score distributions means the scores are significantly different for a particular quality fingerprint [9]. ISO/IEC [10], formalized the idea of performance evaluation of the quality metric, depending on its utility in matching performance. ISO-IEC defines utility of quality metric as degree to which a biometric sample fulfils specified requirements for a targeted application and it should reflect the predicted positive or negative contribution of an individual sample to the overall performance of a biometric system [10].

A. Motivation : Vulnerability of Partial Fingerprints

Partial fingerprints does not only degrades the matching performance but also introduces a security flaw in an authentication system. Roy et al. [11] exploits one such vulnerability. Nowadays, almost every smartphone uses the fingerprints for unlocking the device. The edge devices like smartphones have size constraints, which has led to the miniaturization of fingerprint acquiring sensors. These fingerprint sensors cannot capture the whole fingerprint. Due to the small sensing area of fingerprint acquiring sensors, it only captures some part of the total fingerprint area. In this kind of systems, multiple partial fingerprints of the same user are stored to reduce the false rejections. By making use of multiple partial fingerprints, Roy et al. [11] have generated a Masterprint. This Masterprint surprisingly matches with significant number of other user's partial fingerprints. Specifically, authors have claimed that they were successful in breaking into the 6.88% of user's account in just 5 attempts. This is much higher than the traditional means of authentications like passwords and PINs. Authors have also showed that as the False Match Rate (FMR) increases the possibility of spoofing large number of users, increases significantly. The probability of attacking many users with the help of dictionary attack is much higher when the Masterprints are generated using the partial fingerprints [11].

Bontrager et.al, [12] developed a DeepMasterPrint which is another method of generating Masterprint using the partial fingerprints. This is a deep learning based method, specifically; authors have used the Generative Adversarial Networks (GAN). The Masterprint generated in [11] does manipulation in minutia template. The masterprint generated in [12], is image based. With the help of DeepMasterPrint, authors were successful in spoofing 23% of the users in the database at 0.1% FMR. In addition, with 1% of FMR this spoof rate sharply increases to 77%. The research in [11] and [12] shows that partial fingerprints introduces the vulnerability in fingerprint authentication system. It also points out the abysmal state of fingerprint authentication systems in dealing with partial fingerprints. Joshi et.al, have recently proposed a method for handling the masterprint vulnerability introduced by the multiple instances of partial fingerprints [13]. In this method, the authors have included multiple checkpoints through which the partial fingerprint has to pass which will decide whether the fingerprint is a Masterprint or not. The fingerprint is allowed in the system if it has less than 10 good quality minutia and it does not match with more than 4% of the total users in the database [13].

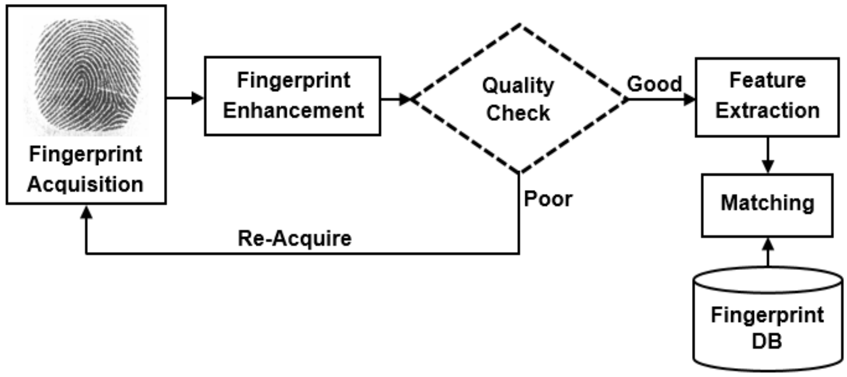

Figure 1. Role of fingerprint image quality module, in the fingerprint recognition system

Though the partial fingerprint vulnerability mitigating systems have started to develop the best way to avoid the security flaw, is to detect partial fingerprints at early stages of the fingerprint recognition system. It is the main motivation behind the research of this paper, which assesses the ability of fingerprint image quality metric to detect partial fingerprints as poor quality fingerprints.

The research work in this paper tries to help decision makers, on which quality metric to use in fingerprint recognition system that reduces the vulnerability introduced by the partial fingerprints. Following are the main research contributions of the paper,

Main Contributions:

- Ranking the available ten fingerprint image quality methods based on their ability to predict matching performance i.e., Utility , in the context of partial fingerprints
- Created a new partial fingerprint dataset by cropping the fingerprint images from FVC 2004 DB1A dataset
- Correlation analysis of fingerprint match scores and the fingerprint image quality is performed for all the ten image quality methods

The organization of the remaining paper is as follows. Section 2, reviews the research work in the fields of the fingerprint image quality and the partial fingerprint recognition. It also discusses the vulnerabilities introduced by the partial fingerprints in a recognition system. Section 3, explains the methodology used for calculating the utility of each biometric sample and its correlation with fingerprint image quality. The section 4 discusses the experimental results on performance assessment of each quality metric, the correlation of quality with utility, number of minutia available in partial and full fingerprints, and Error Reject analysis. The section 5 discusses the main results. Finally, the conclusions of this research are drawn in section 6.

2. Related Work

To deal with the partial fingerprint problem many partial fingerprint recognition techniques are proposed in the literature [14,15,16]. Jea and Govindraju in [14], have proposed an approach which makes use of secondary features derived from minutia information. Partial fingerprint matching needs global structure independent features [14]. Wavelet and SIFT based robust partial fingerprint recognition approach is proposed by Arvindan and colleagues in [17]. The method in [17], applies the Discrete Wavelet Transform (DWT) on an original image, which decomposes image into LL, LH, HL and HH subbands. Then using Scale Invariant Feature Transform (SIFT) the keypoints are detected and matched from LL and HH subbands. Non-linear scale-space based technique, A-KAZE is employed in [18], for solving the partial fingerprint matching problem. The method in [18] uses A-KAZE to obtain the keypoint descriptors, which then matched using the brute force method. They have also used cluster removal technique on matched keypoint pairs to remove false matches. Correlation based approach is proposed by Zanganeh et al. in [19], which computes the similarity between common regions of gallery and probe fingerprint. Existing studies [20] also uses deep learning based techniques to improve the partial fingerprint recognition performance.

Olsen et al. in [21] has done detailed evaluation and analysis of most of the fingerprint image quality metrics available in the literature. Main aim of [21] was to study the features that has high correlation on matching performance. The highly correlated features are used to find the performance predicting ability of quality metrics. The paper uses the Spearman correlation statistic to evaluate quality metrics in terms of the utility [21].

Relation between fingerprint image quality and matching performance in terms of sample utility is analysed in [22,23]. In this, authors points out that the utility based quality metrics are dependent on the matching algorithm used. The correlation between quality value and the match score is the right criterion of assessing performance of quality metric [22].

There are many fingerprint image quality metrics available in literature but how many of them are good at detecting partial fingerprints is still not known. Fingerprint quality assessment for partial fingerprints that are generated due to the small sensor on mobile devices is proposed by Chen et.al [24]. The hybrid framework in [24] uses both the geometric and texture features. Performance measure of quality metrics in terms of utility is widely studied [9, 21, 22], but they have focused on the normal fingerprints, so this motivated us to find the utility of the fingerprint quality from the perspective of partial fingerprints.

This paper attempts to assess the utility of the fingerprint quality metrics in identifying partial fingerprints by assigning them low quality values. In the remaining part of this section, the fingerprint image quality methods are discussed. NFIQ (NIST Fingerprint Image Quality) [25] is the most widely used and publicly available image quality metric. It uses 11 features extracted from the fingerprint image as an input to the Artificial Neural Network. Most of these features are minutia related and taken from the output of the MINDTCT function of the NBIS (NIST Biometric Image Software). This technique is a classification-based technique, which classifies given image into 5 classes where 1 denotes the highest quality and the 5 denotes the lowest quality. Utility of the biometric sample was the main emphasis in developing NFIQ. Due to which, it is expected to be a predictor of the matching performance.

NIST has recently upgraded the version of NFIQ [25], as NFIQ 2.0 [26]. This is a collaborative project initiated by NIST and many other government, public and private entities have contributed to the development of NFIQ 2.0. Like NFIQ, it is again a classification-based technique, which uses OpenCV implementation of the Random Forest Classifier. Many features from the earlier fingerprint image quality methods are considered for training random forest classifier. The random forest algorithm uses total 14 features and match scores from different commercial matchers for an actual training. NFIQ 2.0 gives output values between 0 and 1, where output 1 denotes the high utility and 0 denotes the low utility for a given fingerprint image.

Gabor Feature based Fingerprint image quality metric is proposed by Shen and colleagues [27]. In this, *m* Gabor features are computed for each block in an image. When all *m* Gabor features are relatively same then image block is treated as a poor quality block. When m Gabor features gives relatively different responses then that block is treated as the good quality block. The standard deviation of these Gabor feature blocks are used to segregate each block into foreground and background block. Finally, the quality score is computed as the ratio of the total good quality blocks to the available foreground blocks. In remaining part of the paper this method will be referred as the Gabor Shen (GSH) method. Another Gabor feature based approach (GAB) is proposed by Olsen et al. [28]. In this, Gabor filter is applied with four orientations to an entire fingerprint instead of an individual image blocks. The Quality score is computed as the average of the standard deviations of the four Gabor responses of an entire fingerprint image.

Local Clarity Score (LCS) is the fingerprint image quality metric proposed by Chen et al. in [29]. LCS analyses the ridge and valley clarity as the criterion for deciding a quality value. Well-separated ridge and valley structure depicts the good quality area in the fingerprint. LCS is computed using the separation between the ridge and valley distributions. All these Local clarity scores are combined to compute the Global Clarity Score, which ultimately gives the quality value.

Chen [29] proposed one more method based on orientation flow (OFL) in an image. In a good quality image, the ridge direction flow changes slowly. In this method, the orientation differences of a block with its surrounding blocks are calculated, which is denoted as the local Orientation quality. Then final quality is calculated as the average of all local Orientation Quality values.

Orientation Certainty Level (OCL) [30] is a quality metric, which uses Principle Component Analysis to find the dominant direction in a particular image block. The energy concentration along the ridge valley orientation is computed as the ratio of the Eigen values for the image gradients of a block. The OCL gives the final score value between zero and one, where zero denotes the high energy concentration and the one indicates the low energy concentration. Ridge Valley Uniformity (RVU) is the fingerprint image quality metric proposed by Lim et al. [30]. In this, block wise ratio of ridge and valley thickness is computed. For a good quality fingerprint, this ratio should be consistent and large deviation in it denotes the poor image quality.

In [31], Frequency Domain Analysis (FDA) is employed for calculating an image quality. In this, authors have found that good quality image has single dominant frequency. The poor quality fingerprint has dominant frequency at low frequency values or it does not have any single dominant frequency. Another frequency domain analysis method is proposed in [32]. In this method, 2D DFT is used to transform an image into the frequency domain. Then quality value is computed as the entropy of an energy distribution in the frequency domain where region of interest is defined as an annular band in a power spectrum. Now onward this method is referred as Radial Power Spectrum (RPS) method.

In Table (I), three partial fingerprints from FVC 2004 DB1A dataset along with their quality are displayed for all the 10 fingerprint image quality methods. Here 1, represents Good quality and 5, represents poor quality. The Table (I) shows that NFIQ 2.0 [26] and GAB [28] methods assign low quality values to all three partial fingerprints. NFIQ [25] totally fails in recognizing partial fingerprints and assigns lowest quality value 5, to all the three images.

TABLE I. PARTIAL FINGERPRINT IMAGE QUALITY

Quality Metric	 10_2.tif	 12_2.tif	 31_2.tif
NFIQ 2.0 [26]	1	1	2
GAB [28]	1	1	2
NFIQ [25]	5	5	5
RPS [32]	2	2	4
LCS [29]	3	4	3
OFL [29]	4	4	2
OCL [30]	3	3	4
FDA [31]	4	3	3
RVU [30]	4	4	5
GSH [27]	4	4	5

3. METHODOLOGY

The purpose of this research is to rank available fingerprint image quality metrics according to their performance predicting ability i.e., Utility, when dealing with partial fingerprints. Utility calculates the impact of a particular sample image on the match score. Therefore, utility indicates the biometric performance prediction ability of an individual biometric sample. The utility is calculated as given in equation (1),

$$Utility = \frac{\mu_{genuine} - \mu_{impostor}}{\sigma_{genuine} + \sigma_{impostor}} \quad (1)$$

Where, $\mu_{genuine}$ and $\mu_{impostor}$ are the means and the $\sigma_{genuine}$ and $\sigma_{impostor}$ are the standard deviations of the genuine and impostor scores of an individual biometric sample. For calculating the genuine scores, each sample is matched with all of its other impressions. For calculating imposter scores, first sample of every user is matched with the first sample of the every other user in the dataset, this is the standard procedure specified in all FVC competitions [33]. The high utility value denotes the higher matching performance of a given biometric sample. The utility is calculated for each fingerprint image available in FVC2004 DB1A dataset including partial fingerprints, using the utility equation (1). Main quality methods namely, NFIQ [25], NFIQ 2.0 [26], GSH [27], GAB [28], LCS [29], OFL [29], OCL [30], RVU [30], FDA [31], and RPS [32] are used to compute the quality values of the fingerprints. Finally, correlation between quality values and the utility of the fingerprint image is calculated for each quality method. Higher correlation with the utility denotes that the quality metric is better at predicting matching performance. Performance of a system, after rejecting the lower quality samples is also assessed, which gives clear idea about which quality metric is better at assigning right quality value to the fingerprint images.

A. Data Management

The paper uses the FVC2004 DB1A Dataset [34] for the experimental evaluation. In this dataset, the fingerprints are acquired from 100 different users with eight impressions of each fingerprint, so in total the dataset contains 800 fingerprints. The focus of a research in this paper is on partial fingerprints and the FVC2004 DB1A dataset do not have enough partial fingerprints. Because of this, new sets of partial fingerprints are generated by cropping the original full fingerprints of the dataset. The process to generate the partial instances from full fingerprints is shown in Figure (2). The first step is to detect the foreground of the fingerprint. In foreground estimation, the largest connecting area in the image is detected which is the main fingerprint area. Next step is to crop this foreground image into multiple partial instances. In this paper, three partial images are generated using the third impression of each user from FVC2004 DB1A dataset. The first partial fingerprint is generated by reducing the size of the foreground by 35% from all the sides. The other two partial instances are generated by cropping the first partial instance into two equal parts. The first partial instance is cropped horizontally from the middle, which gives lower and upper parts of the partial fingerprint. Using this partial fingerprint generation process, 300 new partial fingerprints are generated for experimental evaluation. To increase the number of partial fingerprints in the FVC 2004 DB1A dataset, these newly generated partial fingerprints are added to the existing dataset of 800 fingerprints. The experimental evaluations are performed on this new dataset containing 1100 fingerprints.

The main discriminating features used in the fingerprint recognition is the minutiae. For reliable matching the fingerprint should contain enough number of minutiae. The Figure (3) shows the boxplots for the number of minutiae present in the partial and non-partial fingerprints. The partial boxplot shows the number of minutia in the newly generated partial fingerprints. The non-partial boxplot shows the number of minutiae for all the 800 fingerprints of FVC 2004 DB1A dataset. The medians of the two boxplots are significantly different. Overall the non-partial images possess more than 60 minutiae. Whereas the partial fingerprints on an average contains just 20 minutiae. The maximum number of minutiae in partial images are just around 40. The minutiae distributions shown in Figure (3), shows that the generated partial fingerprints does not contain enough minutiae for reliable matching. It also proves that the partial fingerprint generation process used in the paper is effective in creating partial fingerprints.

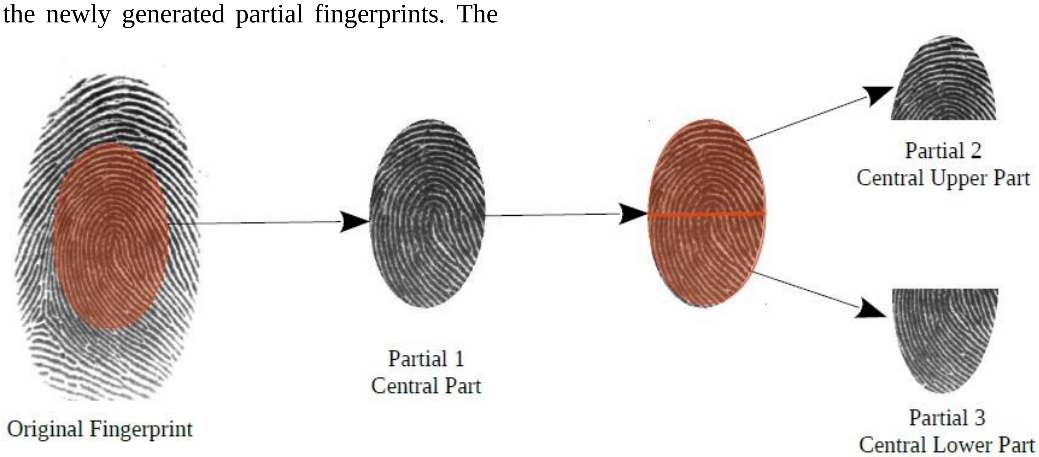

Figure 2. Partial fingerprint dataset creation by cropping full fingerprints from FVC2004 DB1A dataset

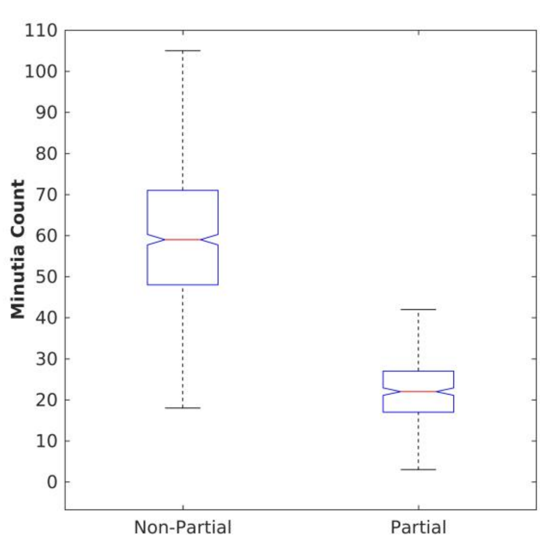

Figure 3. Number of Minutia in partial and non-partial fingerprints

4. EXPERIMENTAL EVALUATION AND RESULTS

The quality metrics used in the experimental evaluation are NFIQ [25], NFIQ 2.0 [26], GSH [27], GAB [28], LCS [29], OFL [29], OCL [30], RVU [30], FDA [31], and RPS [32]. Some of these quality metrics assign higher values for good quality and lower values for poor quality images but others do the reverse. In addition, some quality metrics gives discrete values as output but others gives output in a particular range. Therefore, to make outputs of all the quality metrics uniform, the outputs of each quality method are normalized between 1 to 5 discrete quality values. Where, 5 represents good quality and 1 represents poor image quality so that the higher value denotes higher quality and lower value denotes lower quality.

A. Partial and Non-Partial Fingerprint Performance

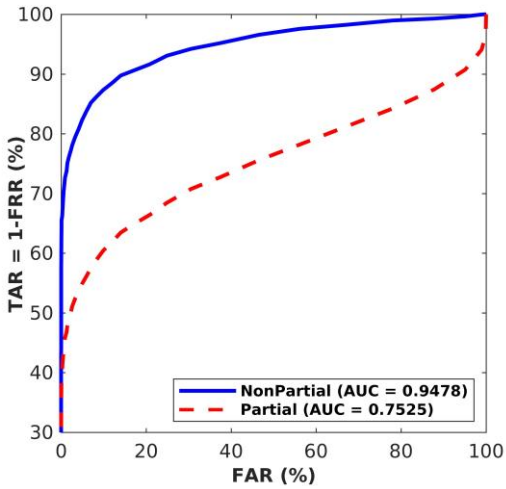

Figure 4. ROC comparison of partial and non-partial fingerprints

In the biometric recognition systems, a threshold is used to decide whether the fingerprint match is successful or not. For high security applications, the threshold is kept very high to ensure high true accept rate (TAR) and low false accept rate (FAR). The Receiver Operating Characteristics (ROC) curve plots the FAR versus TAR. The Figure (4), shows ROC curve for the partial and non-partial fingerprint matching performance. ROC is the threshold independent performance evaluation metric which considers all the thresholds. The partial curve in figure (4) shows the performance, after including newly generated partial fingerprints to the dataset and the non-partial curve shows the performance without including them. The Equal Error Rate (EER) is widely used in the biometric community for evaluating the recognition performance. EER is the error rate of the system when both the false match rate (FMR) and false non-match rate (FNMR) are equal. The lower EER means a better performance of the system. The EER in case of partial fingerprints sharply increases to 29.91% from 11.72% in the non-partial case. There is a sharp increase in the EER of 18.19%. The same thing can be observed in the AUC (Area Under Curve) values, AUC's are 0.9478 and 0.7525 for Non-Partial and Partial cases respectively. This experiment shows that the partial fingerprints heavily degrades the overall performance of the fingerprint recognition system.

B. Correlation of Utility with Quality

For checking, how each quality metric performs in the presence of partial fingerprints, the correlation between the quality and the utility of each fingerprint image is calculated. The ten quality methods are used for calculating the quality of each fingerprint in the dataset. For calculating the correlation, the spearman correlation coefficient technique is used. Two minutia based matchers are used for calculating the match scores, namely Bozorth3 [35] and K-plet [36]. In Bozorth3 matcher, Intra-Fingerprint and Inter-Fingerprint tables are constructed using the minutia location and orientation of probe and gallery fingerprints. Then final match score is calculated by traversing the Inter-Fingerprint compatibility graph [35]. K-plet [36] is again a graph-based method in which a graph is constructed using minutia neighbourhoods. The experimentation uses the MINDTCT function available in NIST NBIS [37], software package for minutia detection. The M1 minutia representation is used, which is the ANSI INCITS standard of storing minutiae of the fingerprint. In ANSI-INCITS standard, an image origin is at the top left and orientation points upwards the ridge ending or bifurcation valley [38].

TABLE II. CORRELATION BETWEEN UTILITY AND QUALITY

Quality Method	Bozorth3 Matcher	K-plet Matcher
NFIQ 2.0 [26]	0.2495	0.2261
GAB [28]	0.2022	0.1856
NFIQ [25]	0.1815	0.2179
RPS [32]	0.1688	0.1208
LCS [29]	0.1674	0.0923
OFL [29]	0.0830	0.0187
OCL [30]	0.0827	0.0528
FDA [31]	-0.1468	-0.1470
RVU [30]	-0.0637	0.0662
GSH [27]	-0.0216	-0.0791

The Table (II) shows the spearman correlation between quality and utility calculated using the Bozorth3 and K-plet match scores. The table (II) shows the NFIQ 2.0 [26] quality metric has more correlation with utility value as compared to other methods in both the matchers used. GAB [28], comes at second place if the Bozorth3 matcher is considered, but it comes at third place when k-plet matcher is used. NFIQ [25], comes at second place when K-plet matcher used and it comes at third place when the Bozorth3 matcher is used. The GSH [27], quality metric has the low correlation with the utility as compared with all the other methods. Typically, the values more than 0.5 are considered as an indicator of moderate correlation between the entities. In addition, values less than 0.5 means the entities are weakly correlated. Most of the values in Table (II) are less than 0.5, this is expected because, matching involves the partial fingerprints. As discussed earlier, the partial fingerprints does not contain enough discriminating features like minutiae, so the match scores are going to be much lesser. However, the purpose of this study is not about the recognition performance, it is about finding the quality metric that handles the adverse condition (presence of partial fingerprint) very well. So it is advised that to look at the correlation values as relative comparison among different quality metrics.

C. Error Reject Characteristics

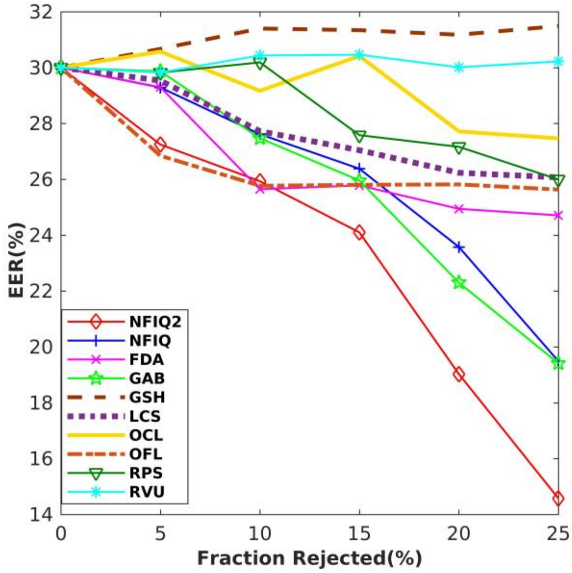

Figure 5. EER of the system after rejecting the lower quality samples for all the fingerprint image quality methods

Error versus Reject curve shows the performance of the system after removing lower quality samples from the dataset. Ideally, all the partial fingerprints should be assigned lowest quality values and when the low quality value samples are rejected, the performance of a recognition system should improve. In this research, 5%, 10%, 15%, 20% and 25% lower quality samples from the dataset are rejected. The Figure (5) shows the error versus reject curves for 10 fingerprint quality estimation methods. The Figure (5) shows that the NFIQ 2.0 [26] has the lowest EER as compared to other techniques after rejecting the lower quality samples. The EER keeps on decreasing from 5% to 25% reject rate for NFIQ2.0 [26], GAB [28] and NFIQ [25] methods as per any ideal quality metric trait. However, there is no consistent drop in EER for all the other studied quality methods. Figure (6), shows the False Reject Rate (FRR) at 1% of False Acceptance Rate (FAR) after rejecting the lower quality samples. The lowest FRR and EER values are recorded for NFIQ 2.0 [26] method with GAB [28] and NFIQ [31] as the closest rivals. The EER values of all the quality metrics at 25% reject rate in Figure (5), does not distinguish between the EER values for the GAB [28] and NFIQ [25] method. However, when the same values are observed in Figure (6), it shows that GAB [28] method performs better than the NFIQ [25] method. The Figures (5) and (6) shows that the GSH [27] quality metric is less effective in detecting partial fingerprints.

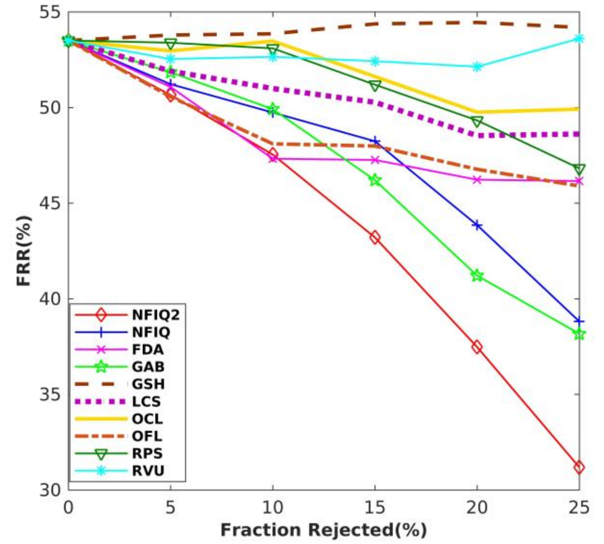

Figure 6. FRR of the system after rejecting the lower quality samples for all the fingerprint image quality methods

D. Performance on Top Quality Fingerprints

This section evaluates the performance of all the Quality metrics when only top three quality Fingerprints are taken into consideration. All the fingerprint images having low quality value i.e., quality 4 and 5 images are removed while calculating the EER and AUC of the system. The Table (III) shows the EER values of all the evaluated fingerprint quality methods after considering only top three highest quality fingerprints. It is observed that GAB [28] shows good performance as compared to all the other existing methods being compared. The experimental results on FVC 2004 DB1A4 dataset shows the EER of 10.1253% for the GAB method as compared with 11.2069% of NFIQ 2.0, which is the second best performer. There is a huge difference between the EER of the first two methods and remaining eight methods. This suggests that GAB and NFIQ 2.0 metrics are very strict at assigning low quality values to the partial fingerprints. One point to note here is that NFIQ, which is widely used fingerprint image quality metric, comes at seventh place, which denotes that NFIQ is not good at predicting matching performance when it is dealing with the partial fingerprints. The top three quality fingerprint experiment also shows that the GSH performs worst as compared with other methods having highest EER of 30.6688.

TABLE III. EER AND AUC PERFORMANCE ON THE TOP THREE QUALITY FINGERPRINTS

Quality Method	EER	AUC
GAB [28]	10.1253	95.6740
NFIQ 2.0 [26]	11.2069	95.5116
FDA [31]	25.4960	80.3009
OFL [29]	25.6895	79.9193
RPS [32]	25.7363	80.9937
RVU [30]	29.7493	75.9346
NFIQ [25]	29.4720	76.0132
LCS [29]	29.5070	76.4478
OCL [30]	30.5490	75.4953
GSH [27]	30.6688	74.6458

E. Execution Time Analysis

TABLE IV. EXECUTION TIME TO COMPUTE IMAGE QUALITY HAVING SIZE OF 480 × 640 PIXELS (THE AVERAGE TIME OVER 20 RUNS IS DISPLAYED)

Quality Method	Time (Milliseconds)
RPS [32]	33
OCL [30]	36
NFIQ [25]	37
OFL [29]	39
RVU [30]	53
GSH [27]	71
LCS [29]	73
FDA [31]	86
GAB [28]	240
NFIQ 2.0 [26]	641

Fingerprint image quality module is used in the early stages of the fingerprint recognition system where the real-time response is expected. The Table (IV) shows the time required to compute fingerprint image quality by using each quality method. A fingerprint image *44_3.tif* from the FVC2004 DB1A dataset is used to compute the execution time. The experiments for execution time analysis are performed on a 64-bits computer with Ubuntu 18.04.2 LTS operating system, Intel(R) Core i7-9700 CPU @ 3.00GHz having 8 CPU cores and 8 GB of RAM. The time execution analysis shows that the Radial Power Spectrum (RPS) [32] method is the fastest quality method that took 33 milliseconds, among all the ten fingerprint image quality methods. Most recent and advanced fingerprint image quality method NFIQ2.0 [26] requires the maximum amount of time i.e. 641 milliseconds. The NFIQ2.0 [26] takes the largest amount of time to execute as compared with other methods because; it uses the features of the other quality methods as an input for computing the quality. The NFIQ [25] method also gives real-time performance which is one of the reason of its wide use in various applications.

5. DISCUSSION

The research findings in this paper shows the vulnerability of the fingerprint recognition system while dealing with the partial fingerprints. To avoid the security threats posed by the partial fingerprints, it is very important to detect partial fingerprints as poor quality fingerprints in the early stages of the biometric recognition. The match scores are not reliable when partial fingerprints are involved. For the reliable matching, only good quality fingerprints should be matched. The main job of the fingerprint image quality metric is to restrict the poor quality fingerprints before the feature extraction and matching stage. The ideal quality method should predict the relative matching performance i.e. Utility, of the fingerprint images. The NFIQ 2.0 [26] method, that uses the features from all the existing fingerprint quality methods, shows good performance. Initially, the NFIQ 2.0 [26] uses many features to train a random forest classifier. The selection of the most important features is performed in an iterative manner depending on the speed and performance predicting ability of the quality method. The NFIQ 2.0 [26] does well in assigning the low quality value because it incorporates the local as well as global features in computing the quality score. The NFIQ 2.0 [26] uses local features such as orientation certainty, frequency analysis, Local quality at minutiae locations, Mean and standard deviation of local features, histogram of local features etc. along with the global features like minutiae count, orientation coherence etc. This implies that for effectively detecting the partial fingerprints both the local as well as global features should be employed. Widely used fingerprint image quality metric NFIQ [25], does not perform well when dealing with partial fingerprints, it assigns higher quality values to most of the partial fingerprints. This happens because NFIQ [25] makes its decision mostly by considering the quality of the foreground blocks. In partial fingerprints, most of the times, foreground part is of high quality but it does not contain enough information which is required for successful matching. Two Gabor based methods are used in the experimental analysis, first method GAB [28] performs well but other GSH [27] performs worst. GSH [27] is less effective in recognizing partial fingerprints because while calculating the final quality score it takes into consideration the number of foreground blocks. GAB [28] considers the fingerprint as a whole and not only the foreground blocks that is why it is better at recognizing partial fingerprints.

The paper has extensively evaluated the ability of the ten fingerprint image quality methods to predict the partial fingerprint recognition performance. The research findings of this paper are going to help the decision makers in selecting the appropriate fingerprint image quality metric especially when partial fingerprints are involved.

6. Conclusion

In this paper, the utility of quality metrics is validated in the perspective of the partial fingerprints. The experimental results of the paper shows that the partial fingerprints highly affects the performance of the fingerprint recognition system and poses security threats. There is a sharp increase in error rate of 18.19% after the addition of partial fingerprints to the existing dataset. The ten existing fingerprint image quality methods are used to evaluate the fingerprint recognition performance in the presence of partial fingerprints. NFIQ 2.0 and GAB method performs well in recognizing partial fingerprints by assigning them lower quality values. Widely used fingerprint image quality metric NFIQ, does not perform well when dealing with partial fingerprints, it assigns higher quality values to most of the partial fingerprints. While designing a fingerprint recognition system, special care should be taken for checking the quality of the fingerprints and this paper gives good indication about which quality metric should be employed for that purpose, especially when dealing with the partial fingerprints.

In future, the research will be focused on a performance predicting fingerprint image quality metric, which is capable of handling partial fingerprints.

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