Automated Clarity and Quality Assessment for Latent Fingerprints

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Abstract

Clarity of a latent impression is defined as the discernability of fingerprint features while quality is defined as the amount (number) of features contributing towards matching. Automated estimation of clarity and quality at local regions in a latent fingerprint is a research challenge and has received limited attention in the literature. Local clarity and quality helps in better extraction of features and assessing the confidence of matches. The research focuses on (i) developing an automated local clarity estimation algorithm, (ii) developing an automated local quality estimation algorithm based on clarity, and (iii) understanding the correlation between clarity and quality in latent fingerprints. Local clarity assessment is performed using a 2-D linear symmetric structure tensor. The goodness of orientation field is proposed to estimate the local quality of a latent fingerprint. Experiments on the NIST SD-27 database show that incorporating local clarity information in the quality assessment improves the performance of the matching system.

1. Introduction

Latent fingerprints are important crime scene evidences used by forensic experts. Matching latent fingerprints, using an Integrated Automated Fingerprint Identification System (IAFIS), is a semi automated process involving manual annotation of features and manual verification of results. During February 2013, FBI's IAFIS received a cumulative number of 16858 latent prints for matching and the average response time for each print is *1 hour, 45 minutes and 30 seconds* [1]. This suggests that manual processing of all these fingerprints is an arduous and time consuming process. Therefore, scalability is a major challenged faced by large scale latent fingerprint matching systems. However, not many of these submitted latent prints may have the required information for making a correct match. During the capture of live-scan fingerprints, quality assessment is performed at the sensor level to check for the quality of captured fingerprints before registration in the gallery. Such a quality test is very useful for latent fingerprints as well.

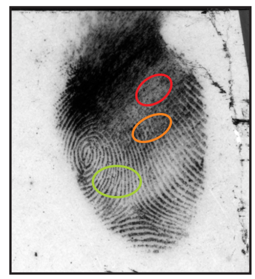

Figure 1. A latent fingerprint sample from the NIST SD-27 database [3]. The print has 39 manually annotated minutiae and is labeled as a "good quality" latent print according to the global measure. However, the clarity and quality in local regions vary from good (green region), bad (orange region), and ugly (red region).

In the ACE-V procedure for manual matching of latent fingerprints [9], during the first analysis stage the prints are marked as either (i) Value for Individualization (VID) having sufficient information for matching, (ii) Value for Exclusion Only (VEO) which needs further processing, and (iii) No Value (NV) which can be discarded. The main advantages of assessing the quality of latent fingerprints are as follows:

- Quality assessment acts as a cue to check whether the captured latent fingerprint is suitable for further analysis. Recently, Ulery et al. [12], performed an analysis to understand the sufficiency of information for latent fingerprints and show that prints with less than five minutiae may not be suitable for further analysis.
- Quality assessment can assist in feature annotation. By providing the quality (global or local), the annotators would have the meta information to analyze for more informative features in high quality regions than in low quality regions, as shown in Figure 1.
- Boosting the matching performance using quality is well studied in literature [5].

Quality, in fingerprints, is generally measured by the amount of discriminable information available in the given image. In latent fingerprints, quality has received limited attention in the literature. Hicklin et al. [8] conducted a large scale survey of examiners on latent fingerprint quality assessment. The study involved 86 experts manually annotating 1090 latent prints. These annotations were studied to develop guidelines, metrics and software tools for assessing fingerprint quality. Yoon et al. [14], proposed a semi-automated global quality assessment algorithm for latent fingerprint. The procedure involved analyzing the local ridge pattern continuity, which weighted along with the number of minutiae provided a global quality value. The quality measure was used to classify latent fingerprints as VID and non-VID images. The experiments conducted on a combined database of NIST SD-27 [3] and WVU databases [10] provided an average classification accuracy of 88% for manually annotated minutiae. Recently in 2013, Hicklin et al. [7] highlighted the interchangeable use of "quality" in biometrics and forensic community and introduced the notion of "clarity" as used by forensic experts. Clarity of a latent fingerprint is the ability to differentiate between the presence or absence of features while quality is the amount of matching features (say, minutiae) present.

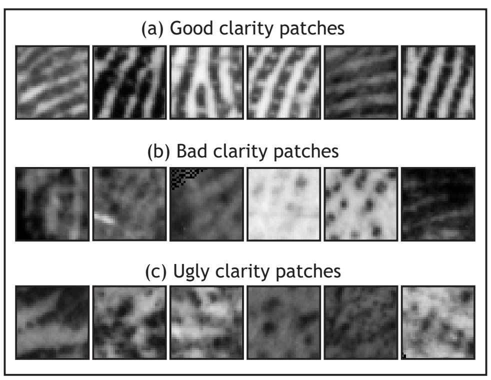

Figure 2. Sample patches of size 32×32 from latent fingerprints of the NIST SD-27 database [3]. It can be observed that based on the visibility of ridge patterns, local patches can be grouped as good clarity, bad clarity, and ugly clarity patches.

As shown in Figure 2, high clarity regions may not have enough number of features and may be of poor quality. Further, Hicklin et al. [7] built a software tool, LQAS (Latent Quality Assessment Software), to enable examiners to manually annotate the local quality and clarity maps of a latent print. A study on human performance suggests that there is a strong inter-examiner inconsistency in marking clarity of a latent fingerprint suggesting that an automated system might be more robust.

1.1. Research Contributions

In this research, we propose an automated local quality assessment algorithm for latent fingerprints. The research contributions of this paper are three fold: (1) an automated algorithm to assess the local clarity of latent fingerprints, (2) an automated algorithm to assess the local quality of latent fingerprints using *local clarity*, and (3) understand and analyze the correlation between clarity and quality assessment.

2. Proposed Algorithm

The proposed local quality assessment is a two step algorithm:

1. **Ridge clarity assessment:** Clarity assessment refers to visual discernability of the features irrespective of the presence or absence of features. Clarity provides a sense of confidence of the annotated features.

2. **Ridge quality assessment:** Quality assessment refers to the quantity and amount of features present in the given local region.

In this context, quality scores are a non-biased estimator of the match score and the matching performance, while we hypothesize that the clarity scores are a non-biased estimator of the quality score. It means that in high quality latent fingerprints, matching can be performed with increased confidence; same as in high clarity regions, quality can be estimated with increased confidence.

2.1. Local Clarity Assessment

As illustrated in Figure 2, regions having good interleaving patterns of ridges and valleys are visually more clear than regions with smudges, strokes, and other noises. A 2-D structure tensor can be used to capture the uniform ridge and valley patterns in a region [5]. Given an image (latent fingerprint) $f(x, y)$, a second order structure tensor encodes the first order geometric patterns [6]. Both the orientation information, using gradients of f, $\nabla f = [f_x, f_y]$ and its confidence can be captured using a linear second order structure tensor. The gradient structure tensor, J, is calculated at every point (x, y), by Cartesian product of the gradient vector $[f_x, f_y]$ with itself as shown in Equations 1, and 2.

$$J = \nabla f(x) \nabla f(x)^T \tag{1}$$

$$J = \begin{bmatrix} f_x^2 & f_x f_y \\ f_x f_y & f_y^2 \end{bmatrix} \tag{2}$$

The eigen analysis of the structure tensor J, helps in analyzing the presence of local linear symmetry in images. The structure tensor J is decomposed to obtain its eigenvalues $[\mu_1, \mu_2]$ and the corresponding eigenvectors $[\lambda_1, \lambda_2]$. It is understood from the literature [13], that the larger eigenvalue shows the strength of the local image edges and the

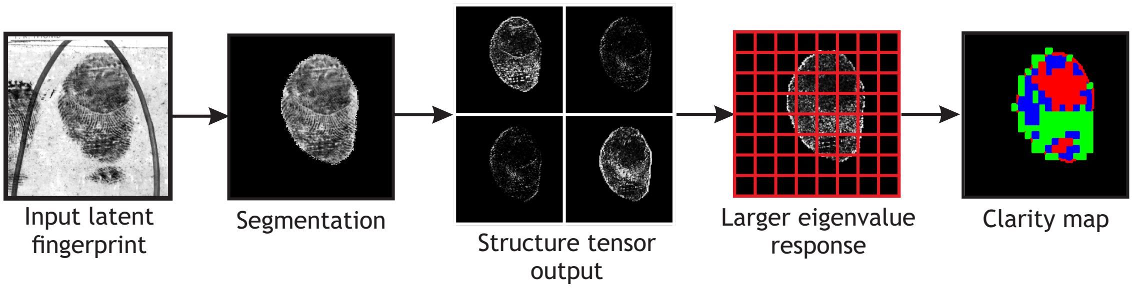

Figure 3. Illustrating steps involved in the proposed local clarity assessment algorithm for a sample latent fingerprint from the NIST SD-27 [3].

corresponding eigenvector points across the edge (in gradient direction). Hence, as shown in Equation 3, the maximum eigenvalue is averaged over the local neighborhood Ω, with N_Ω pixels, and is denoted as the clarity of that region.

$$f_{LC,\Omega} = \sum_{\Omega} \frac{\mu_{1,\Omega}}{N_\Omega} \quad (3)$$

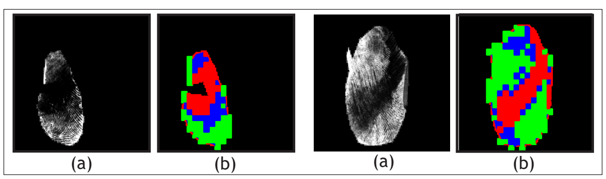

Figure 4. Local clarity maps for sample latent fingerprint from NIST SD-27 [3] with (a) input latent fingerprint and (b) output clarity map. In the clarity map, green color denotes the regions of good clarity (level-2 and level-1 features can be marked with confidence), blue color denotes bad clarity (only level-1 features can be marked with confidence), and red color denotes poor clarity (neither level-2 nor level-1 features can be marked).

The overall clarity map is heuristically divided into three clarity bins as follows:

1. **Good clarity (Level-2)**: Regions where both level-1 (ridge flow) and level-2 (minutiae) features are clearly markable.

2. **Bad clarity (Level-1)**: Regions where only level-1 (ridge flow) features are clearly markable.

3. **Ugly clarity**: Regions where both level-1 (ridge flow) and level-2 (minutiae) features are not visible.

The detailed, step by step algorithm is discussed in Algorithm 1 and the overall process is illustrated in Figure 3. Sample local clarity maps for two latent fingerprint examples from the NIST SD-27 database are shown in Figure 4.

Algorithm 1 Local clarity assessment for latent fingerprints

Input: $f(x, y)$ is the segmented latent fingerprint.
Process: Assessment of local clarity of latent fingerprints using the local ridge pattern strength.
1. Smooth the latent fingerprint using a Gaussian filter, G with variance $\sigma = 0.5$.
2. Calculate the gradient vector of the Gaussian smoothed image $\nabla f = [f_x, f_y]$, along x and y-axis independently.
3. Calculate the 2-D gradient structure tensor at every pixel in the block using Equation 2.
4. Decompose the structure tensor to obtain its eigenvalues $[\mu_1, \mu_2]$ and the corresponding eigenvectors $[\lambda_1, \lambda_2]$ such that $\mu_1 > \mu_2$.
5. The average of the larger eigenvalue μ_1 over the local block Ω is the clarity value in that block, as shown in Equation 3.
Output: A clarity map, f_{LC}, of the latent fingerprint.

2.2. Local Quality Assessment

In literature, global quality metrics have been proposed for quality assessment of latent fingerprints. These approaches primarily use features such as the number of minutiae (level-2 feature) and the total area of minutiae region for quality estimation and classify latent prints in {*Good, Bad, Ugly*} [3] or {*VID*,$\overline{VID}$} [14] categories. However, these features cannot be used for local quality estimation. In this research, we therefore propose a local quality measure based on the fitness of the orientation field (level-1 feature). Two different quality estimation methods are proposed - with and without incorporating the clarity measured in the previous section. Following the hypothesis that clarity is a non-biased estimator of quality, it is our assertion that incorporating clarity should help us to better estimate the local quality of a latent fingerprint.

2.2.1 Local Quality Without Clarity

Let $f(x, y)$ be the given segmented latent fingerprint image and $\nabla f = [f_x, f_y]$ be the gradients of f in x and y-direction calculated using the Gaussian derivative filter. The gradient phase (orientation), θ, is calculated at every pixel of the fingerprint image using Equation 4.

$$\theta = tan^{-1}\left(\frac{f_y}{f_x}\right), \theta \in \left(0, \frac{\pi}{2}\right] \tag{4}$$

The image, f, is tesselated into non-overlapping blocks of size Ω. The phase angle is split into five bins in the range $\left(0, \frac{\pi}{2}\right]$ and the histogram, $hist_\Omega$, is computed for every local block. The cell, ω, consists of a neighbourhood of 3×3 blocks, with the center block as reference, and the average histogram, $ahist_\Omega$, is calculated for the cell using Equation 5, where N_ω is the number of blocks in the cell.

$$ahist_\Omega = \sum_{\Omega \in \omega} \frac{hist_\Omega}{N_\omega} \tag{5}$$

The average histogram represents the consistency of orientation flow in the neighbouring blocks with respect to the reference block and can be visualized by a peak in the average histogram. As shown in Equation 6, the fourth order moment of the histogram (kurtosis) is calculated to measure the "peakedness" of an average histogram. This peakedness provides the quality of the local fingerprint region, $f_{Q,\Omega}$ where μ_h and σ_h are the mean and variance of the average histogram, $ahist_\Omega$.

$$f_{Q,\Omega} = \frac{E(ahist_\Omega - \mu_h)^4}{\sigma_h^4} \tag{6}$$

where $E(x)$ represents the expected value or mean of x.

2.2.2 Local Quality With Clarity

In the above quality assessment technique, the confidence with which the orientation is assessed is considered to be uniform throughout the image. However, in better clarity regions, orientation flow can be assessed with higher confidence than in poor clarity regions. In Equation 5, the histogram in each block of the cell, is weighted by the corresponding local clarity value to compute the weighted average histogram, $whist_\Omega$, as shown in Equation 7.

$$whist_\Omega = \sum_{\Omega \in \omega} \frac{f_{LC,\Omega} \times hist_\Omega}{N_\omega} \tag{7}$$

The updated local quality, after incorporating local clarity, is measured by obtaining the kurtosis of the weighted average histogram, $whist_\Omega$ as shown in Equation 8.

$$f_{QC,\Omega} = \frac{E(whist_\Omega - \mu_h)^4}{\sigma_h^4} \tag{8}$$

The step by step description of the proposed local quality assessment algorithm is presented in Algorithm 2.

Algorithm 2 Local quality assessment using local clarity for latent fingerprints

Input: $f(x, y)$ is the segmented latent fingerprint and $f_{LC}(x, y)$ be its local clarity map.
Process: Assessment of local quality of latent fingerprints using the local clarity of ridge patterns.
1. Smooth the latent fingerprint using a Gaussian filter, G with variance $\sigma = 0.5$.
2. Calculate the gradient vector of the Gaussian smoothed image $\nabla f = [f_x, f_y]$, along x and y-axis independently.
3. Compute the gradient phase (orientation) of the fingerprint image, in the range $\left(0, \frac{\pi}{2}\right]$ using Equation 4.
3. Split the image into non-overlapping blocks of size Ω and for each block compute the five bin histogram, $hist_\Omega$ of the orientation.
4. For every block, the neighboring 3×3 blocks is considered as a cell, ω. Weighted normalized histograms, $whist_\Omega$, for each cell is calculated and assigned as the reference block using Equation 6.
5. The kurtosis i.e., $4th$ order moment, of the weighted normalized histogram, $whist_\Omega$ is computed for each block as shown in Equation 7, which provides the quality of the local block.
Output: A quality map, f_{QC}, of the latent fingerprint.

3. Experimental Results

The proposed local clarity and local quality based assessment algorithm are evaluated on the NIST SD-27 database [3]. NIST SD-27 database is a publicly available latent fingerprint database having 258 latent prints, with each of them manually labelled as $\{$*Good, Bad, Ugly*$\}$. The database consists of 88 good, 85 bad, and 85 ugly quality fingerprints. These global quality values are assigned based on the number of manually annotated minutiae available with the database. All the images are manually segmented by drawing a contour around the latent impression. All the experiments are performed on the segmented latent fingerprints. The estimated local clarity map is evaluated using the ground truth clarity map annotated by the authors. It is also studied whether the clarity helps in minutiae annotation by comparing the minutiae confidence with the predicted clarity. Finally, the influence of quality and clarity on the matching performance of latent fingerprint is studied.

3.1. Clarity vs Ground Truth Analysis

To create the ground truth of the local clarity map, manual annotation is performed by the authors.[1] To perform

[1]The segmented images and the manually annotated local clarity maps will be made publicly available for researchers.

manual annotation, a GUI based tool is developed which allows the expert to mark every local block of size ω with clarity label - {*Good, Bad, Ugly*}. Using the proposed local clarity estimation algorithm (Algorithm 1) the clarity value for each block is calculated. Table 1 shows the confusion matrix between the estimated clarity and ground truth clarity values for a total of 27308, 32×32 size blocks from the NIST SD-27 database images.

Estimated clarity	**Ground truth clarity**		
	Good	Bad	Ugly
Good	2453	2330	7412
Bad	1546	1593	4868
Ugly	596	792	5718

Table 1. Matrix comparing the ground truth clarity maps with the estimated clarity maps for latent fingerprints from NIST SD-27.

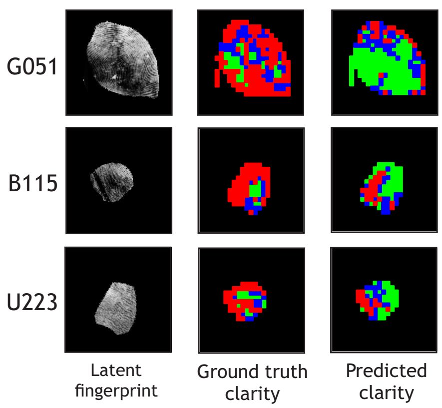

Figure 5. Manually annotated ground truth and estimated local clarity maps for sample latent fingerprint from the NIST SD-27 [3]. One sample fingerprint from *Good, Bad, and Ugly* latent fingerprints are chosen. During manual annotation, it can be observed that the experts have high thresholds [11] in marking good clarity regions thereby resulting in very few green colored blocks. In the clarity maps, green color denotes good clarity, blue color denotes bad clarity, and red color denotes poor clarity regions.

It can be observed that out of 27308 blocks, in manual annotation there are only 4595 (16.8%) good clarity blocks while the predicted clarity maps have 12195 (44.65%) good clarity blocks. This suggests that during annotation, experts tend to have a high threshold [11] in marking good clarity blocks, resulting in very few good clarity blocks whereas the algorithm follows an optimistic approach. This can be visually observed in Figure 5.

3.2. Clarity vs Minutiae Analysis

In the NIST SD-27 database, each manually annotated minutia is assigned one of the three confidence values [4]: {good, medium, poor} quality. There are in total 3429 good quality, 1304 medium quality, and 490 poor quality minutiae. Although, this value is named as the quality of a minutiae, it represents the confidence with which the corresponding minutia is marked. According to the NIST SD-27 documentation [4], *"Quality was to be rated based on the condition of the image in the location in which the minutiae was positioned and based on how clearly identifiable the type of the minutiae was in the range"*. The condition of the image in the local region resembles our definition of clarity. Hence, the good clarity regions predicted by our algorithm, where both level-1 and level-2 features are markable, should correspond to the good quality minutiae annotated. Experimental results show that out of 3429 good quality minutiae, 2301 (67%) minutiae are positioned in the estimated good clarity regions. In the manually annotated clarity maps, there are only 800 (34.8%) minutiae positioned in the good clarity regions. Thus, the proposed clarity assessment algorithm is more optimistic and provides better estimate of the confidence of a minutia.

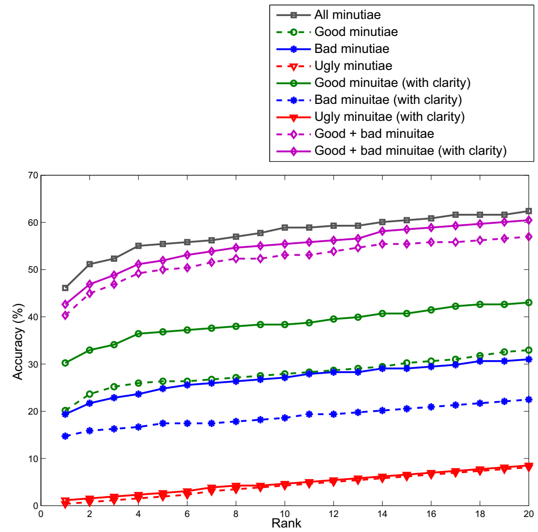

Figure 6. Rank-20 CMC curve of matching latent fingerprint from the NIST SD-27 to the rolled fingerprints. The stroked lines show the matching performance of quality distribution obtained without using clarity while full lines use quality distribution after using clarity information.

3.3. Quality vs Match Performance Analysis

The eventual aim for estimating the quality is to improve the performance of a fingerprint matching system. The two objectives of the experiments performed in this section are: (i) analyze whether the proposed quality score is a good predictor of the matching performance and (ii) validate whether incorporating clarity provides a better estimate of matching performance. Existing tenprint feature extractors generally produce spurious minutiae in latent prints. NIST-SD27 has a mean of 21 manual minutiae while NBIS and Verifinger produce an average of 138 and 252 minutiae, respec-

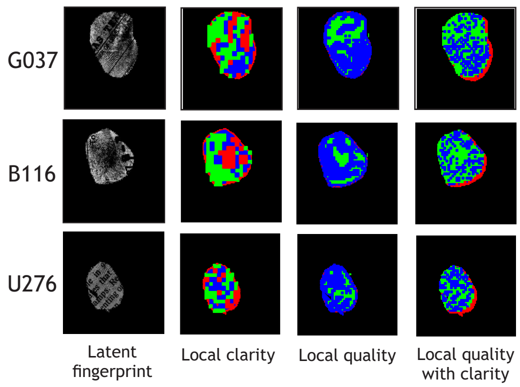

Figure 7. Visual comparison of clarity and quality maps assessed using the proposed algorithm for sample latent fingerprints from the NIST SD-27 [3]. One sample fingerprint each from *Good, Bad, and Ugly* latent fingerprint are chosen. The effects of incorporating clarity during quality assessment can be observed in the last column. In both the clarity and quality maps, green color denotes good clarity, blue color denotes bad clarity, and red color denotes poor clarity regions.

tively. Hence, in our experiments, latent fingerprints are matched with the corresponding rolled fingerprints of the NIST SD-27 database, with the manually annotated minutiae and *bozorth3* of NBIS [2] as matcher. We also perform matching with minutiae found only in good quality regions, minutiae in bad quality regions and minutiae in poor quality regions. The rank-20 Cumulative Match Characteristics (CMC) curve in Figure 6 shows that better matching performance is obtained using the minutiae present in good quality regions compared to bad or poor quality regions. It is to be understood that the best performance is obtained by using all the minutiae, which is the highest possible as all the minutiae in this experiment are manually marked. Automated algorithms try to emulate this performance. In this experiment, we attempt to study if the different quality bins are a good predictor of the match score. The same experiment is repeated for the quality score which uses the local clarity, as explained in Algorithm 2. The clarity information helps in better estimation of quality thereby improving the matching performance of the system. When quality is assessed using clarity maps, the performance of good quality minutiae is improved and that of the bad quality minutiae is decreased. This suggests that clarity assists in better estimation of local quality. It can also be visually observed in Figure 7. Also, when the ugly minutiae are removed from matching, the performance of the system is decreased by only 2%.

4. Conclusion

In this research, a local clarity estimation and a local quality estimation algorithms are proposed for latent fingerprints. The effect of incorporating local clarity in quality assessment is studied. It is experimentally shown that local clarity assists in better estimation of local quality thus resulting in improved matching performance. We plan to extend this research by getting feedback from multiple forensic experts to better design the clarity assessment algorithm. We also plan to combine level-2 features with level-1 features for local quality estimation.

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