

Latent Fingerprint Identification Using Deep Learning Method

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ABSTRACT

Digital fingerprint is one of the most consistent modalities in up to date biometrics and hence has been broadly studied and deploy in real applications. The accuracy of one Automatic Fingerprint Identification System (AFIS) largely depends on the quality of fingerprint samples, as it has an important impact on the degradation of the matching (comparison) error rates. This thesis generally focuses on the evaluation of biometric quality metrics and Fingerprint Quality Assessment (FQA), particularly in estimating the quality of gray-level latent fingerprint images or represented by minutiae set. By making a refined review of both biometric systems and relevant evaluation techniques, this contribute by the definition of a new evaluation or validation outline for estimating the performance of biometric quality metrics. It is defined to check the quality of latent fingerprint images by statistically measured parameters. In this work, an automatic Region-Of-Interest (ROI)-based latent fingerprint quality assessment technique is proposed by using deep learning. The first stage in our model uses deep learning, namely Region Convolutional Neural Network (R-CNN) to segment a latent fingerprint. In the second stage, feature vectors computed from the segmented latent fingerprint are used as input to a multi-class perceptron that predicts the value of the fingerprint. This proposed approach eliminates the need for manual ROI and feature markup by dormant examiners. Finally, experimental results on NIST SD27 show the effectiveness of our technique in latent fingerprint quality prediction

Keywords: Region of interest (ROI), Deep Learning Region Convolutional Neural Network(CNN), Fingerprint Identification

I. INTRODUCTION

Biometric authentication is a security process that relies on the unique biological type of an individual to verify that he is who is says he is. Biometric authentication systems [11] compare a biometric data capture to stored, confirmed valid data in a database

If both sample of the biometric data match, verification is confirmed. Typically, biometric authentication is used to manage data sample and access to physical and digital resources such as buildings, rooms and computing devices. The oldest known use of biometric verification is fingerprinting. Thumbprints made on clay seals were used as a means

of unique detection as far back as ancient China. Modern biometric verification has become almost instantaneous, and is more and more accurate with the advent of computerized databases and the digitization of analog data. Biometric technologies are becoming the base of an extensive array of highly secure identification and personal verification solutions. As the transaction crime action [11] take place. and raise the level of security infringes, the necessity for highly secure identification and personal verification technology are becoming apparent. Biometric-based solutions are able to provide for private financial transactions and personal data privacy. The necessity for biometrics can be found in,

state and local governments, federal, in the military, and in commercial applications. Enterprise wide network security infrastructures, government IDs, secure electronic banking, investing and other financial transactions, retail sales, law enforcement, and health and social services are already Profit from these technologies.

Biometric-based validation applications include workstation, network, and domain access, single sign-on, application logon, data protection, remote access to resources, transaction security and Web security Trust in these electronic transactions[12] is important to the all over the world. It is integrated with other technologies such as smart cards, encryption keys and digital signatures, biometrics is set to pervade nearly all aspect of the economy and our daily lives utilize biometrics[12] for personal authentication is becoming suitable and considerably more accurate than current methods (such as the utilization of passwords or PINs). biometrics devices can be access the process to a particular individual password and token may be used by someone other than and easily hacks the password by the authorized user).

II. LITERATURE SURVEY

TITLE	ADVANDAGE	DISADVANDAGE
Latent Fingerprint Value Prediction: Crowd-Based Learning [3]	Automatic fingerprint identification system accuracy is high	Processing time is high.
Latent Fingerprint Image Segmentation using Fractal Dimension Features and Weighted Extreme	False Detection Rate (FDR) is less. MissedDetection Rate (MDR) is also less.	It requires additional features to improve classification accuracy of the fingerprint patches from bad and ugly latent fingerprints.

Learning Machine Ensemble[4]		
Latent Fingerprint Image Segmentation Using Deep Neural Network [5]	Highest accuracy. Reduced FDR and MDR.	It requires advanced algorithms for feature extraction latent fingerprints.
Automated Clarity and QualityAssessm et for Latent Fingerprints [6]	The local clarity assists in It better estimation of local quality thus resulting in improved matching performance.	The accuracy is less.
Latent fingerprint image Quality [7]	AFIS with high accuracy.	The use of manually annotated minutiae makes their quality assessment
Automatic Latent Fingerprint Segmentation [8]	It boosts the hit rate of a state of the art COTS latent fingerprint matcher.	It requires combining orientation information to get instance segmentation for segmenting overlapping latent fingerprints.
Segmentation and Enhancement of Latent Fingerprints: A Coarse to Fine Ridge Structure Dictionary[9]	It ables to improve the performance of two COTS ten fingerprints	Computational efficiency of the algorithm is less.
Enhancement of Latent Fingerprint	It access scalability, accessibility and	Image quality is less.

Images with Segmentation Perspective [10]	flexibility	
Latent Fingerprint Segmentation Based on Ridge Density and Orientation Consistency [11]	Less computational complexity.	Highest MDR and FDR. Less identification rate.
A New Metric for Latent Fingerprint Image Preprocessing [12]	It performs well in the measurement of the latent fingerprint image's quality.	Computation efficiency is less.

III. SYSTEM IMPLEMENTATION

A. SEGMENTATION USING R-CNN

R-CNN is the structure blocks for the outlook deep learning model. Faster R-CNN uses a Object detection peecess.and CNN use to detect image and feature extractor to extract image features. Then it uses a CNN region proposal network to create ROIs. We apply ROI pooling process identify the clarity of image to warp them into fixed dimension. It is then feed into fully linked layers to make classification and boundary box prediction. and also detect the true values patches in boundary box.The R-CNN builds all the base works for feature extractions and ROI proposals. At first, performing image segmentation may require more detail study to colorize the image segments. After the ROI pooling, we add 2 more convolution layers to build the mask.

Another major input of Mask R-CNN is the improvement of the ROI pooling. In ROI, the warping is digitalized: the cell boundaries of the cell. Fully connected layers divided into two categories

they are Soft max Function means identify the possibility of true values and fake values. Boundary box means store the true value.

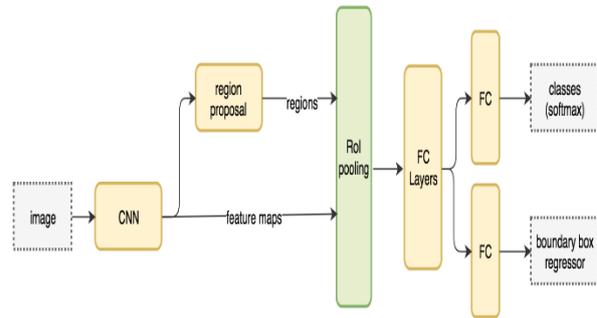


Fig 1. Architecture of R-CNN

In this phase, latent fingerprint image is divider into 8x8 non extend beyond patch by using R-CNN. Stochastic features that model a sharing over image patch are learnt using a generative multi-layer feature extractor. The features are used to train a single layer perceptron classifies the patches into Biometric and non-Biometric classes. The fingerprint patches are used to rebuild the latent fingerprint image and the non-biometric patches which contain the ordered noise in the new latent fingerprint is neglected. The segmented latent fingerprints from this stage are used as inputs to the quality estimation stage. The choice of patch size of 8x8 for the segmentation stage is based on its optimal.

B. QUALITY ASSESSMENT

In the quality appraisal stage, 32x32 patch are extract from the segmented fingerprints ROIs and features compute from them are used as the value appraisal training dataset. The choice of 32x32 is based on the fact that for 500 pixels per inch (ppi) imagery, the width of a pair of ridge and valley is 8 to 12 pixels wide. This imply that a patch size of at least 24x24 pixels is required to cover two ridge with a valley in among. Given a segmented latent fingerprint image L, let g, b, u be the number of its 32x32 patches classify into bins B1,B2,B3, respectively.

Let val = max{g, b, u}. The quality of L is defined as:

$$Q(L) = \begin{cases} 1, & \text{if val} = g; \\ 2, & \text{if val} = b; \\ 3, & \text{if val} = u. \end{cases} \quad (5.1)$$

Ties are broken in an optimistic manner. For example, if $g = b$ and $b > u$, then $Q(L) = 1$. image extracted from patches determined biometric good bad or ugly

C. FEATURES USED FOR QUALITY ASSESSMENT

The local features used for latent fingerprint quality estimation are shown in Table C

Table C. Local features used for latent quality assessment

Features	Description
Peak and Mean Kurtosis,	Kurtosis of image patch
Peak and Mean Slewness,	Skewness of image patch
Ridge frequency and thickness, Ridge-to-valley	sinusoidal model of ridges and valleys in the image patch
Orientation certainty level	Measure of strength
Spatial consistency	compute from the image patch

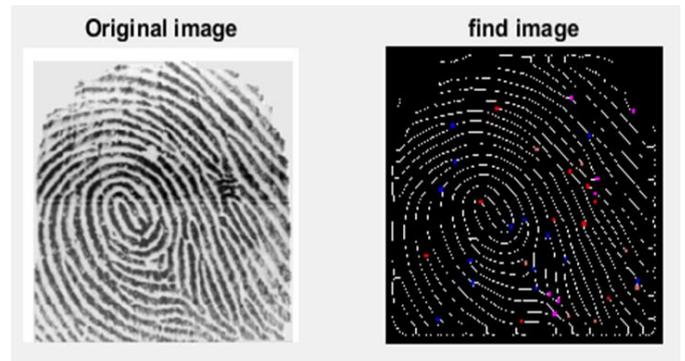
IV. RESULTS OUTCOME

A. LATENT FINGERPRINT DATABASE

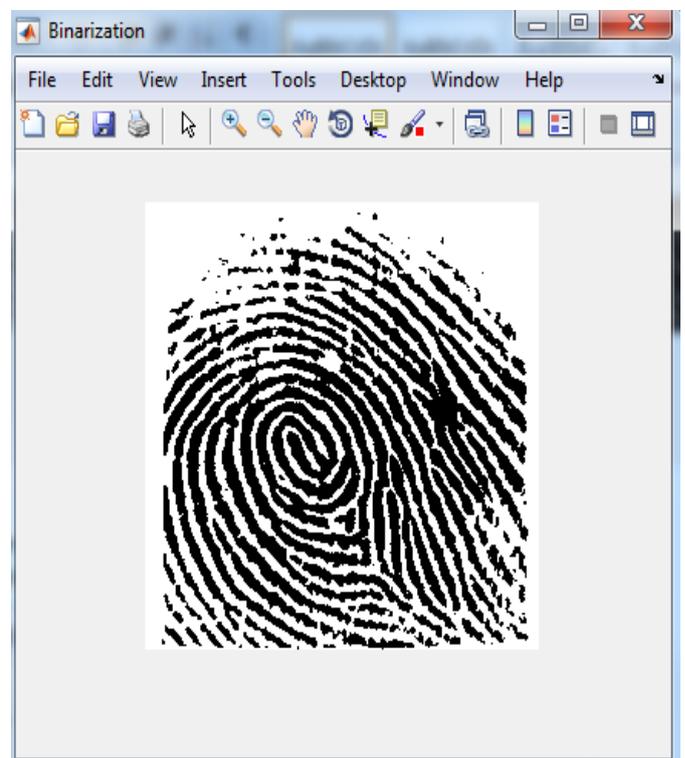
The ROI segmentation the fingerprints and quality review stages of our model were trained, validate and tested on NIST SD27 dormant fingerprint database. This database contains descriptions of 258 latent fault scene fingerprints and their matching rolled ten prints. The images are group into high quality, low quality and middle quality categories. The group is based on the quality of the image definite by latent examiners. NIST SD27 has 88 Good, 85 Bad and 85 ugly quality latents. The hidden prints or roll prints are at 500 ppi.

The training ,justification and testing of the segmentation part of the model was done with 232,000 8x8 patches (132,000 for preparation, 50,000 for validation and 50,000 for testing) from the NIST SD27 database with 40% from high quality 30% from middle quality, and 30% from low quality NIST image category.

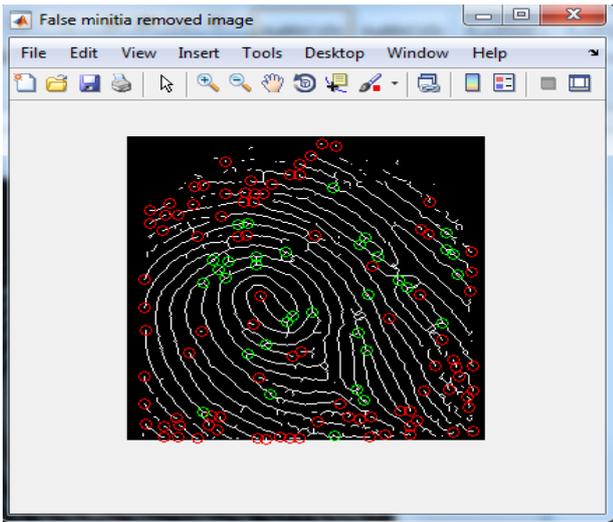
B. Original Image



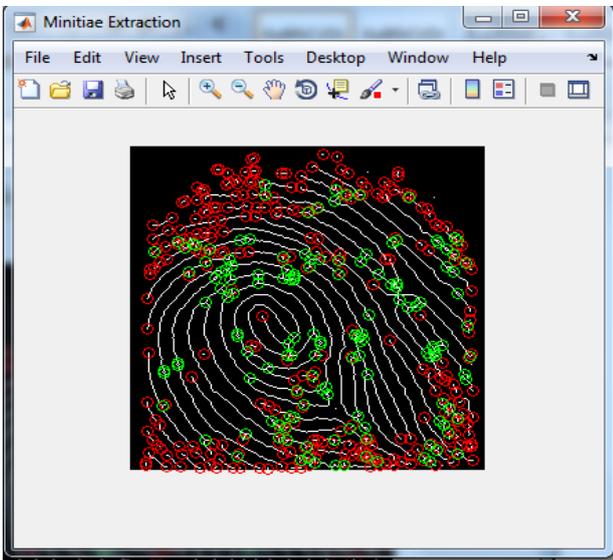
C. Binarization



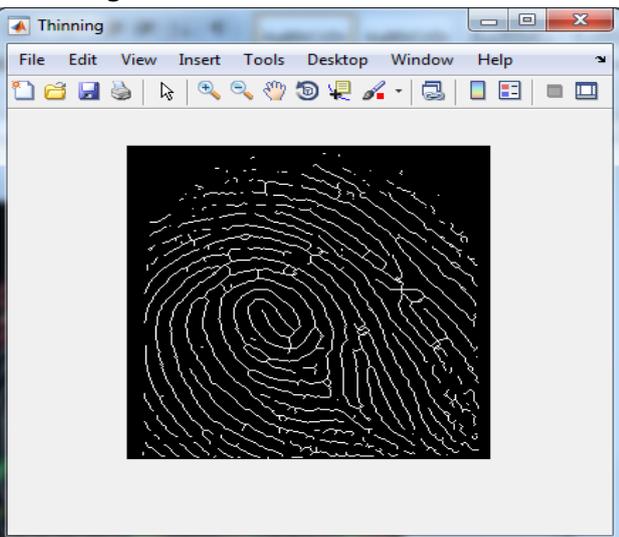
D. False Minitia Removed image



E. Minitiae Extraction



F. Thinning



V. DISCUSSION

A. MISSED DETECTION RATE (MDR)

This is the profit of class C_1 patch and set C_2 patch and it has show(6.1)

$$MDR = \frac{FN}{TP+FN}$$

Where FN is the number of false negatives and TP is the number of true positives

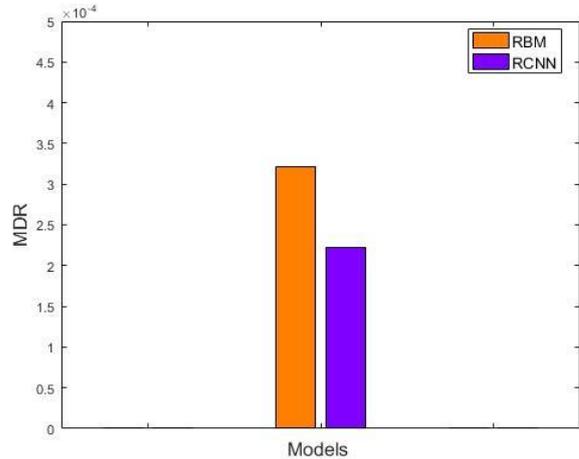


Fig 2. Comparison of MDR

Figure. 2 shows the comparison of existing RBM-based latent fingerprint quality assessment and proposed R-CNN based latent fingerprint quality assessment technique in terms of MDR. From this graph, it is observed that the proposed R-CNN based latent fingerprint quality assessment technique achieves less MDR compared to the existing RBM-based technique.

B. SEGMENTATION ACCURACY (SA)

It depend one Phase and second phase

$$SA = \frac{TP+TN}{TP+FN+TN+FP}$$

For the segmentation phase, C_1 = fingerprint, C_2 = non-fingerprint, and for the value assessment stage, $C_1 \in \{high-quality, low quality, middle quality \}$ and $C_2 \in \{ high-quality, low quality, middle quality \}$.

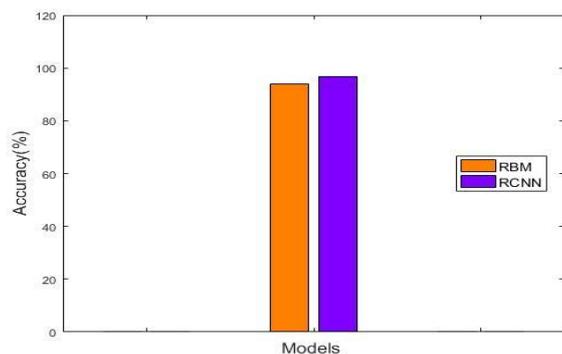


Figure B. Comparison of Accuracy

VI. CONCLUSION

In this section, the conclusion decides that the proposed technique is better than the existing technique in terms of higher performance. In the existing system, stacked RBM is used for segmenting latent fingerprint features followed by a multi-class perceptron based classification to predict the latent fingerprint image quality. However, RBM has high complexity to train well and also has difficulty to estimate the partition functions to the same resolution images. To avoid above-mentioned issues, we propose, an automatic Region-Of-Interest (ROI)-based latent fingerprint quality assessment technique is proposed by using deep learning built by R-CNN. Initially, R-CNN is used to segment a hidden fingerprint appearance by remove the necessity for physical ROI markup and manual feature gain by latent examiners. After that, characteristic vectors calculate from the segmented latent fingerprint are used as contribution to a mult-class perceptron that predict the value of the fingerprint. Finally, the experiment results on NIST SD27 prove the efficiency of our technique in latent fingerprint quality prediction. and concluded that the proposed R-CNN based latent fingerprint quality assessment technique achieves higher accuracy, precision, recall and less MDR, FDR significantly.

VII. FUTURE WORK

The future extension of this technique would integrate additional features to further increase the accuracy. It detects eye, face, hair, ear, etc improve the performance of fingerprint.

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