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BIO-METRIC IDENTITY BY CONTACTLESS AND CONTACT-BASED MATCHING WITH CONSERVATIVE FINGERPRINT IMAGES

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***Abstract*—To defend state borders and backup e-governance programs, enormous databases of contact-based fingerprints have been generated. Contactless fingerprints sensors are becoming more popular because they provide a greater cleanliness, security and accuracy. The existing method have capacity to match contactless 2D fingerprints with legacy contact-based fingerprint databases is critical to the adoption and success of such contactless fingerprint technologies. This research looks at the issue and proposes a novel method for reliably matching fingerprint scans. The project consists of a robust thin-plate spline model that was a incorporated for the correction of deformations to address contact based and contactless sensor interoperability problems. The robust thin-plate spline (RTPS) is a new type of spline that can be more correctly describe elastic fingerprint deformations. The RTPS-based generalized fingerprint deformation correction model (DCM) is presented to correct such deformations on contact-based fingerprints. When DCM is used, essential minutiae element on both contactless and contact-based fingerprints are aligned accurately. Incorporating minutiae-related ridges into such cross-matching performance will be researched further. In addition, we create a new database of 1800 contactless 2D fingerprints and the associated contact-based fingerprints obtained from 300 clients, which is made public ally available for further research. Using two public ally available databases, the experimental results provided in this work confirm our approach and produce outperforming results for matching contactless 2D and contact-based fingerprint photos. Automated detection and correction of perspective distortion in contactless fingerprint images is expected to reduce the error rates. This work incorporates more robust core detection algorithms and powerful match strategy.**

Keywords- **Biometrics, contactless fingerprint sensor interoperability, Deformation correction model (DCM), e-governance, and Robust thin-plate spline.**

I. INTRODUCTION

Identification of people is a requirement for both personal and property security. Naturally, people recognize and identify each other by some distinctive characteristics such as face and gait. These and many other cues are also used in automated systems to identify people and they are called biometric traits.

Biometric traits are reliable identifier because they cannot be easily lost, stolen or forgotten like knowledge or possession-based authentication mechanisms. There are many kinds of biometric traits and in general, they are grouped into two categories: physical and behavioral traits. While physical traits include fingerprint, face and iris. Behavioral traits include gait, signature and writing behavior.

Fingerprints have all the necessary properties to be used for reliable and high scale identification. They are unique to each other persons in the world; even identical twins have different fingerprints. Ridges or valleys on the fingers can be easily captured by using various imaging techniques and sensors. Due to the sweat and oil surface on the finger skin, they are left on the surfaces and can even be collected from where they make physical contact.

Due to those properties of the fingerprints mentioned above, they have earned a crucial role in various areas of usage. Primarily in forensic and security. With increasingly large and mobile populations, the manual work required for matching has also increased and even become impossible. As the result, with the guidance of the approach that the experts use, automated fingerprint recognition identification systems (AFIS).

In the literature, several promising methods for fingerprint sensor interoperability and estimating/correcting fingerprint deformations have been presented. However, this is an issue that requires further attention are the reviews of earlier works.

There has been almost nil attention to develop effective algorithms to accurately match fingerprint images acquired from the contactless and contact-based fingerprint sensors, i.e., ensure interoperability between contact-based and contactless fingerprints. The fingerprint matching algorithms introduced in the literature to match fingerprint images from different fingerprint sensors or with rolled fingerprint images deliver very limited performance when employed for matching contact-based fingerprints with contactless 2D fingerprint images.

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The methods that use TPS model to correct the fingerprint deformations on the contact-based fingerprints are computationally complex and fail to correct the fingerprint deformations relative to the ground truth. As a result, the fingerprint matching techniques introduced in the literature, for cross-sensor fingerprint matching, only can deliver limited improvement in performance while matching fingerprint images acquired from contact-based and contactless fingerprints sensors.

II. PROPOSED METHODOLOGY

Fingerprint recognition is a very challenging task because of high intraclass variance and interclass similarity. In order to cope with this challenging problem. It is broken down into several steps such as fingerprint classification, orientation extraction, fingerprint Enhancement, Minutiae Extraction. This study focuses on the fingerprint classification and minutiae extraction since they are the two most fundamental steps for accurate matching without manual feature extraction and preprocessing.

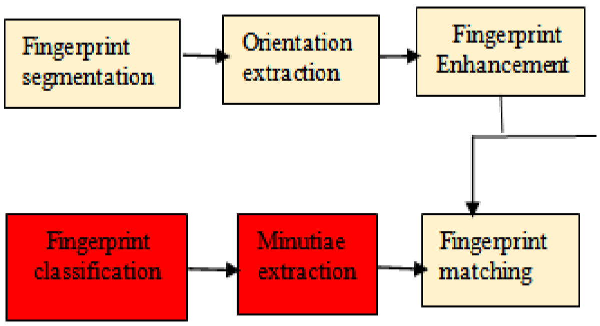

Figure: Fingerprint recognition pipeline

The skin at the fingerprint has a wavy, indented structure. It contains protruded lines with different curvature and dented areas between those lines which are called **ridges** and **valleys** respectively. Fingerprints are the imprints of those ridges and valleys and the pattern they create cause fingerprint to have different and distinctive details. In general, those details are grouped into three levels at different scales:

Level 1features are global features that the ridge lines shape. These features are called singular points and there are two types of singular points: **delta** and **loop.** As seen in figure loop is the inflection point of the parallel ridge lines and delta is the triangular area where different ridge lines meet. In addition, the upper -most singular point is called the **core.** The shape and location of these are not unique to each fingerprint rather they help to describe course level shapes which are useful for grouping fingerprint.

Level 2 features are local where the ridge line characterized change at a finer level. These features are called **minutiae points** and they provide the fingerprints the bulk of their distinctiveness. There are many types of minutiae points however the two most important and mostly used are **ridge ending** and **bifurcation.** A ridge ending is the name implicates where a ridge ends and a bifurcationis where ridge lines split into two ridges like a fork. Those two types of minutiae points are illustrated in figure.

Level 3features are observed at the finest level and they mainly consist of very tiny details such as sweat pores. These features also make a high contribution to the uniqueness of the fingerprints. Although their distinctiveness is very high, they may be misleading because they are so small and hence very difficult to locate accurately. The image resolution should be very high to use these features as a proper means of identification.

i. Fingerprint classification

For automated fingerprint identification. most of the time, a large number of comparisons is needed where the query fingerprint is compared with all existing fingerprints in the database. Because fingerprints are used mostly in forensics, the number of fingerprints in the database is counted by millions most of the time. Reducing the search space is critical for both reducing search time and increasing the matching accuracy. Fingerprint identification system since it aims at reducing the search space by assigning predefined classes to fingerprints. According to Henry classification system, there are 5 classes of fingerprints

- **Arch**
- **Tented Arch**
- **Left Loop**
- **Right Loop**
- **Whorl**

These classes are determined by the singular points in the fingerprint. According to the location and amount of the singular points and the ridge flow orientation, fingerprint classes can be assigned. In details, the **Arch class** has no singular points. It has a smoother curvature and nearly parallel ridge lines that are a little bit curved around the center of the fingerprint. **Tented Arch** class is similar to Arch class visually but the curvature is higher and it has one delta and one loop. The delta is located directly below the loop and is vertically aligned with it**. Left loop and Right loop** also have one delta and one loop however they differ from each other. **Whorl class**, unlike other classes, may have two deltas and two loops. Additionally, the ridge curvature makes a 360° tour around the center. The search space gets very small because of the natural distribution of the classes among the people. only 3.7% of the people have

Arch and 2.9% have Tented Arch class while majority have left loop. Right loop and Whorl (33.8%,31.7% and 27.9% respectively).

Fingerprint classification is a course level matching. Since the features that it relies on the global and not distinctive. It cannot be directly used for accurate matching. However, it isuseful for determining which fingerprint can be eliminated from the dataset due to having different classes. Thus, it helps to reduce the search space.

ii. Fingerprint Matching and Minutiae Extraction

Fingerprint Matching is the core stage of fingerprint recognition. The main objective is to match the input with the enrolled fingerprints in the database and detect or confirm the identity of the person. However, this is a challenging task since fingerprints have large intraclass variance. i.e., same fingers may create very different impressions. This is mainly due to the following are the main reason:

- **Displacement:** Fingerprints may be located in different places in the paper/sensor. Even though some sensors guide strict placement into a specific area. Very small displacement may cause large difference pixel wise.

- **Rotation:** Similar to displacement. Fingerprints may be rotated while transferring to paper or obtaining via sensor.

- **Partial Overlap:** Because of displacement, rotation or other factors. Some parts of the fingerprint may not be visible. When the obtained impressions are not coming the fingerprint fully. It may cause fingerprints to look very differently.

- **Non-linear Distortion:** Because of the 3D shape and elasticity (rubber like structured) of fingers. Fingerprints may be distorted when pressed against a 2D surface like paper or sensor.

- **Variable pressure:** When pressing the finger to the sensor or paper, the pressure may vary. This causes variations in the fingerprint impressions.

- **Changing skin conditions:** While capturing the fingerprint via ink and paper or a sensor. The finger skin may be wet, dry, or oily. These factors affect the ridgelines thickness in the impressions.

- **Noise:** While obtaining the fingerprint via sensor, there may be internal noise caused by the sensor. Also, the paper might be noisy or while taking the photo of the paper or scanning it. Some noise might be introduced to the fingerprint.

- **Feature Extraction Error:** Prior to fingerprint matching. Some features are extracted such as ridge orientation field. Singular points and minutiae point or some preprocessing is applied to the fingerprint.

B: Related Work

i. Fingerprint Classification:

Many approaches have been developed to classify fingerprints and in most of them. The fingerprint classification is divided into two main tasks:

- Feature Extraction
- Classification

The majority of the methods focus on ridge line flow, orientation image, singular points and Gabor filter response.

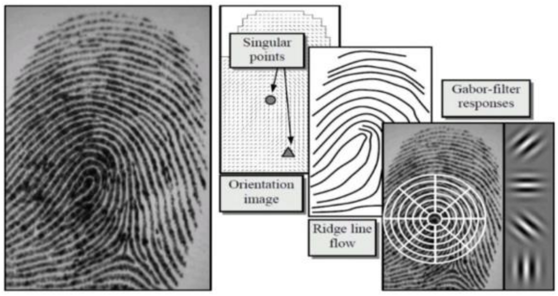

Figure: some features of fingerprint that are used for fingerprint classification

Classification methodologies are coarsely classified into six categories according to it:

- **Rule based approaches**
- **Syntactic approaches**
- **Structural approaches**
- **Statistical approaches**
- **Neural Network based approaches**
- **Multi classifier approaches**

Rule-Based Approaches are based on singular points. Because singular points differ in number and location among fingerprint classes. The classes can be assigned to their relative positioning. In Kawagoe and Tojo use Poincare index for detecting singular points

Syntactic approaches, the patterns are represented with symbols and a grammar over the symbols. Using the grammar, fingerprint classes are assigned. In Moayer and Fu used a symbol set obtained from orientation image patches. With a class of context-free grammars, they describe fingerprint patterns and this allows classification.

Structural approaches are based on higher-level representations of features such as graphs or trees. In Maio and Maltoni propose an approach that segments orientation images into similarly oriented partitions and constructs a relational graph by making each region a node and connecting those nodes.Using inexact graph matching techniques. The graph and the model graph classes are compared. In the

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figure,the steps of the algorithm are shown. use a template-based graph matching instead of relational graphs. In order to create homogeneous regions, they exact set of dynamic masks are used to calculate a cost function and the cost function is used for classification. Their approaches can handle translation and rotation.

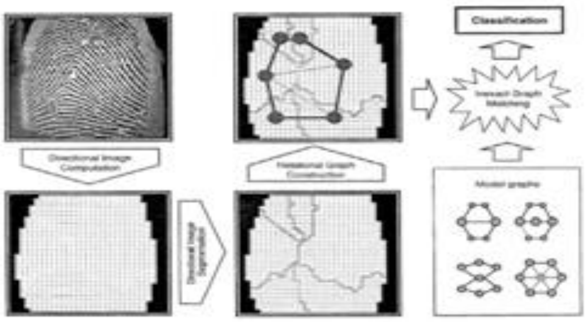

Figure: The steps of methodology used by Maio & Maltoni

Statistical approaches feature vectors are extracted from the images and used in statistical classifiers such as SVM or k-nearest neighbor(k-NN) algorithm. In Luo et al,used k-NN to classify the feature vectors obtained by using Curvelet transform (CT) and gray-level co occurrence matrix (GLCM). They achieved 94.6% accuracy for five-class classification problem and 96.8% accuracy for four-class classification problem with 1.8% rejection.

Neural Network based Approaches, earlier application consists of using multi layer perceptron's and small fast forward neural networks. With the emerge of deep learning. In [20], conic Radon Transform is used as a feature extractor. CRT is applied on the fingerprint images and the original images are used as inputs for the CNN. They achieved 96.5% accuracy on 4-class classification.

Multi classifier approaches, in order to improve the performance multi classifier are combined. In [18] Jain Prabakar and Hong propose Finger code which is a 192-dimensionalrepresentation of fingerprint derived from local ridge structures. Using the dimensional representation of fingerprints derived from local ridge structure. Using the finger code, the fingerprints are classified with two stage classifiers. They use k-NN in the first stage and multi neural networks in the second stage.

ii. Minutiae Extraction

Many different approaches have been developed for minutiae extraction for many years. These will be coarsely analyzed into two groups.

- **Traditional Methods**
- **Deep Learning-based Methods**

Traditional methods mostly extract features manually which require domain knowledge. Additionally, most methods perform on preprocessed fingerprint images.

In [24], Farina et al, propose an approach that uses binarized and then skeletonized fingerprint images. In their method, they clean ridge bridges using a novel method in which ridge positions are used instead of directional maps. Then, the reliability of the extracted minutiae points is assessed for matching. Their algorithm performs the following steps for the extraction of minutiae points.

In [26], Jiang Yau and Ser propose an algorithm that traces gray-level ridges by using piece-wise linear lines of different lengths. In some selected points, they smooth the fingerprint image with an adaptive -oriented smoothing filter. They detect minutiae points while tracing the ridges and forming skeleton. In the skeleton image. each ridge gets a number and the ridge numbers are associated with minutiae points. This helps in the post processing step to eliminate spurious minutiae points according to spatial structural and ridge relationships.

With the emergence of deep neural networks, researches shifted their focus using **deep learning** on minutiae extraction. In [27], Jiang et al, proposed using deep convolution neural networks with a patch-based approach. They train two sequential networks: the first one is Judge Net which detects the candidate minutiae points. They use 45*45 and 63*63 sized patches with minutiae and non-minutiae labels determined according to center 27*27 pixels.

For minutiae extraction, unfortunately, there is not a common benchmark dataset as we have for fingerprint classification. The only dataset that was available with ground truth minutiae points is FVC2002. Therefore, the results of this study are only comparable with [31]. It is a difficult process to obtain database manually marked minutiae points.

III. EXPERIMENTAL RESULTS

i. Feature Classification

In this section, performance of the models is reported in terms of accuracies and confusion matrices. Results are shared under the experimental context (dataset sizes) in terms of maximum performance. The results are interpreted all together and a more detailed analysis is performed in terms of the fingerprint classification domain.

Results for different dataset sizes

In this experiment, all models are trained with 5 different training set sizes:125,250,500,1000, and 2000. The test dataset size remains the same i.e... 2000 image. The proportion between classes are also kept the same in differently sized training sets in order to have the same uniform distribution among the classes and not to effect accuracies with class imbalance. The expectation is that with the growth in dataset sizes, the model performs better.

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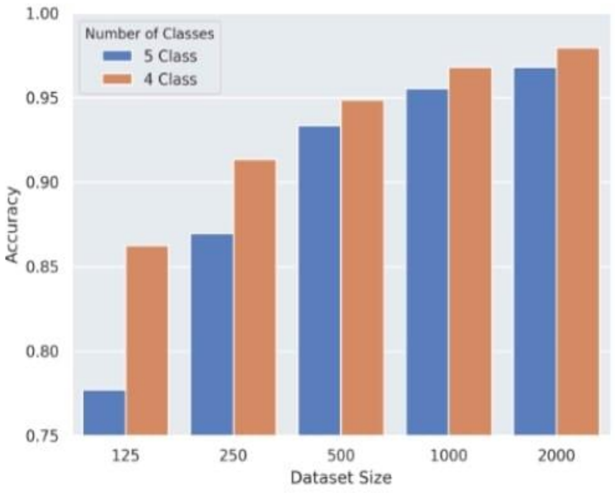


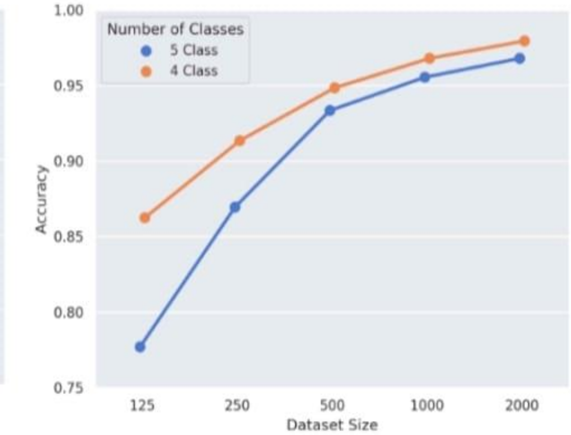


Figure: Accuracies of models trained with different dataset sizes

ii. Minutiae Extraction

The experimental setup is constructed with 50*50 patch sizes, two non-minutiae patch extraction approaches minutiae at all and no minutiae model with two model types. Example is shown in below figure.

When the first approaches are adopted in 50*50 patch size that the patches are generally taken from the sides and areas in the fingerprint images with very few minutiae points. More informative parts i.e., core areas of the images and the parts where the minutiae points are close and frequent are not sampled.

The center core areas carry more information because ridges are more intense at those parts and the curvature changes are also high.

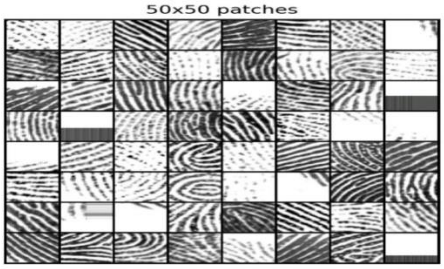
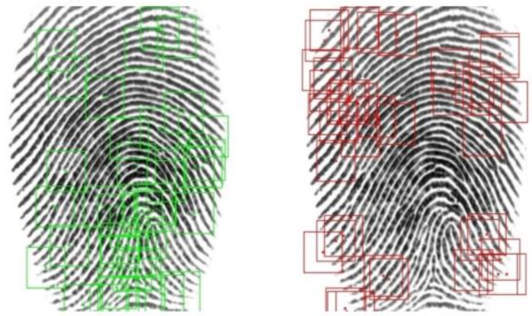


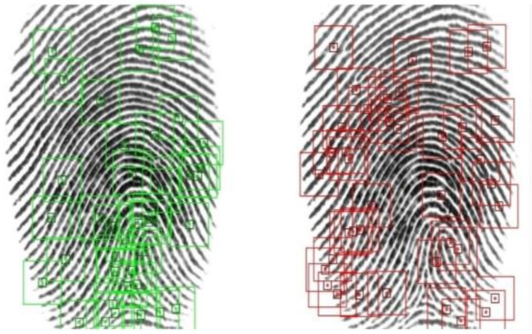
Figure: patch example of 50*50

In 50*50 patch sizes, the first approach shown below, it can be seen that non-minutiae are not taken from the center of the fingerprint image where many minutiae points are observed.



Figure(a): 50*50 patches with non-minutiae patches that do not contain minutiae points

By applying second approaches, the samples are more uniformly distributed over the full-size image.



Figure(B):50*50 patches with non-minutiae patches that do not contain any minutiae points at 10*10 center

IV. CONCLUSION

In this study, deep learning systems are developed for fingerprint classification and minutiae extraction. The main aim is to analyze performances of deep learning system under different conditions. Deep learning reduces the need for manual work and domain knowledge required before training fingerprint systems. Analysis is done on the effects of dataset sizes.

For fingerprint classification, different deep learning architecture are deployed to analyze the effect of model complexity. Additionally, the models are trained with different dataset sizes in order to observe the impact of number of training samples. The results showed that deep learning is a good method for fingerprint classification and the models can be achieved state of the art results.

The performance results are shared in terms of accuracy and confusion matrices for fingerprint classification. The highest accuracies for 5-class and 4-class models are observed to be 96.8% and 97.95% respectively.

For minutiae extraction, a patch-based classification approach is adopted. The result is shared in 50*50 patch sizes with two different non minutiae patch extraction approach and minutiae does not contain any minutiae points at 10*10 center.

All in all, for both fingerprint classification and minutiae extraction, it is observed that deep learning is a good methodology. Experiment results show that with the adoption of deep learning, very satisfactory results can be achieved. These results are also promising for applying deep learning for other steps of th4 fingerprint recognition pipeline.

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