A CNN Based Model for Fingerprint Cross Matching

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Abstract

Nowadays, images can acquired from different type of sensors. These sensors can be categorized into contact-based and contactless. Many application field of fingerprint recognition use various type of sensors. Due to the accuracy, hygiene and less deformation, emergence of contactless fingerprint sensors are increasing. So the cross matching of fingerprints from these two type of sensors are very important in various field. We proposes a new architecture for the cross comparison of contactless to contact-based fingerprints. The proposed architecture is based on convolutional neural network (CNN).This architecture use pre-processed fingerprint images for the feature extraction. Proposed architecture contain three subnets with Siamese CNN. Each subnet use ridge map as well as the minutia map as the input. Final score obtained from the each subnet is use to calculate the overall performance of the system. The evaluation is done on the publicly available dataset with contactless fingerprints corresponds to contact-based fingerprints. The experimental result shows that proposed method gives better performance when compared to traditional methods.

Keywords: *CNN, Image Processing, Ridge Map, Minutiae Map.*

1. Introduction

Fingerprint is a key marker, which plays a major role in proving the identity of a human, because of its constant and unique features. Biologically, fingerprints can be defined as a unique skin pattern that remains as a printed identification form in palm of every human. There will not happen any change in pattern and structure of fingerprint while aging. Due to all these reasons, fingerprint recognition technologies taken as an important human identification method. Applications like law enforcement and e-business takes advantages of this technique.

Nowadays different types of fingerprint sensors are available with different industries. There are optical sensor, laser sensor etc. for taking fingerprints. These sensors capture the ridges of fingerprints. Ridge features are just one category of features when considering fingerprints.

But several industrial areas uses contactless fingerprint matching techniques. The fingerprints stored in their database may be contact based. So additional sensors need not be deployed to match fingerprints. Instead, just one monitoring camera is enough. Contact-less fingerprints do have several features. Since these are images, we can apply several image processing techniques to extract new features.

Fingerprint interoperability is very important. Fingerprint interoperability means the ability to check the cross match of fingerprint from two different sensors. Proper examination and gaining a wide knowledge about different steps and algorithms used in Fingerprint Recognition techniques is the goal of this paper. The key feature used for these type of methods are minutia feature because of its accuracy. Nowadays we need to match the fingerprint from different types of sensors, so more sophisticated methods are needed. We discussed some important methods from old to now.

The main objective of this paper is to build a CNN based fingerprint cross matching model with great feature strength.

2. Related Works

There are number of papers related to the fingerprint recognition and cross matching. Each paper shows that better similarity checking. In paper [3] author presents a system considering sensor interoperability, which means the capability of a device to match the images from different sensors. This system used a Thin-plain-spline (TPS) model, which helps to handle the distortion in fingerprint images. Paper [4] discuss about non-contact based acquisition and construction. Here the 3-D view of image is build using a mosaicking method. Mosaicking of multiple view of a finger follows some steps present in [4]. This results better matching score. Paper [5] consider sensor interoperability as well as the fusion score. Normally the similarity checking of fingerprint images from different sensors results low performance. So here [5] the authors used fusion score from multiple sensor before usual pre-processing and feature extraction steps.

Paper [7] proposes an algorithm to cross match the fingerprints from multiple sensors. To extract the minutia feature, ridge of fingerprint core point used and it is used for the cross comparison. Core detection method used for find out the core point. The major step in this paper [7] is that, adjustable bounding box method is used for minutia matching. Paper [8] proposes a minutia based cross matching method and also proposes better pre-processing methods. It will check for the distortion correction, if it needs do the correction otherwise directly extract the minutia features. In paper [9] minutia with three descriptors are extracted. That are Gabor-HoG, BGP and orientation feature. During the matching step, minutia as well as the three descriptors are separately matched to calculate the score. A field orientation based cross correlation approach is used in the paper [10]. Gabor filter and canny filter used to smoothing and edge detection respectively. Matching score is calculated using this cross correlation method. In paper [6] a new deformation correction model (DCM) introduced. It is based on Robust-thin-plate spline (RTPS), which helps to understand and acquire the exact elastic deformation of fingerprint with the use of splines. Aligning process of contact-based and contactless fingerprints are done by this DCM. Combination of minutia feature with ridge map provides a better cross matching performance.

3. Proposed System

3.1. Proposed Model

The proposed system in figure 1 includes same parts in the existing system [1], but it use better extraction algorithm for the extraction of minutiae feature. Minutiae extraction method in the [11] used in existing system. The proposed system used a cross numbering method for minutiae information collection.

Data pre-processing, Ridge and Minutiae extraction, CNN model training and validation, and Average accuracy calculation of the model are the parts included in this project. Major steps included:

1. Data Pre-processing: down sampling, ROI calculation and Gabor filtering of both contactless and contact-based images.
2. Ridge and Minutiae feature extraction of both contactless and contact-based images.
3. Building three Siamese CNN model and its training and validation.
4. Average accuracy calculation of three CNN model.

Data pre-processing is an important step in image processing. The need of pre-processing is to compensate any imperfections in the image. This will helps to improve the performance and accuracy of image processing. Various types of pre-processing steps are available in this area. Here, fingerprint images also need pre-processing to extract the ridge and minutiae feature perfectly.

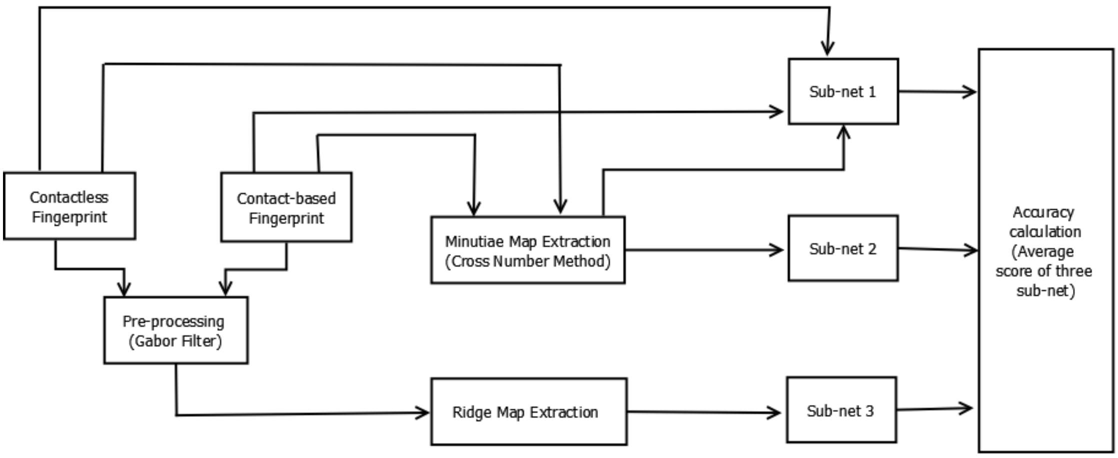

Figure 1. Block Diagram of Model

The pre-processing steps used is that, down sampling, region of interest calculation, and Gabor filtering. Down sampling is done to ensure size similarity in both contactless and contact based fingerprint images. ROI (region of interest) automatically calculated by selecting the center portion of image. Gabor filter is a linear filter use to smoothing and texture analysis. It helps to identify the ridges present in fingerprint. Figure1 shows such images.

Ridges and minutiae for each human is unique. So, it can use for unique identification of each person. Figure shows the minutiae of a fingerprint. In case of contact-based sensors, output is ridge map of fingerprint. Ridges contactless images are extracted by applying Gabor filter.

Steps followed for ridge filtering.

1). Normalization of image and ROI calculation.
2). Finding orientation of every pixels in the image.
3). Finding overall frequency of ridges.
4). Creation of Gabor filter and filtering process.

Minutiae feature are commonly used in every fingerprint recognition method. Due to its accuracy. Here two types of minutiae are extracted, edge point and bifurcation points. Edges are ending of a ridges and bifurcation is convergence or divergence of ridges.

Steps followed for minutiae extraction.

1). Create two array for edge and bifurcation minutiae and initialize with zero.
2). Dividing enhanced images into 3*3 blocks.
3). Calculate cross number for each pixel.
4). If Cross number value is one, insert that pixel value to edge array, otherwise goto step
5). If cross number value is three, insert that pixel value to bifurcation array.

This cross matching network is the core part of the project. Network is made up of three sub-nets. Each sub-net include two CNN sharing same weight. Siamese CNN is a CNN sharing same weight and takes a pair of input, this will be from two different image. The model used here is taken from [1]. This model creation done in python. Each CNN include four convolution layer and max pooling layer. Convolution layer do some filtering on the input. Max pooling do down sampling on output from the convolution layer. Filter size of convolution layer are 11*11, 7*7, 5*5, 3*3 respectively.

Layers included in each CNN are listed in table. The main layers in this network are convolution layer, max pooling layer, concatenation layer, and fully connected layer or dense layer. Convolution layer do filtering with different filters and give output to max pooling layer. There it will do down sampling and kernal size is 3*3. Fully connected or dense layers are the last layer in a cnn, where will get a feature vector. Some extra layers are also includes like activation layer, normalization layer dropout layer. Activation layer includes any activation function used in the neural network. Here, it is ReLU, rectified linear unit. Nowadays ReLU is commonly use in neural networks, because it is six times better than the sigmoid activation function. The main advantage with which is that, it only activate some neuron at a time. This activation function can apply on hidden layers or at the end of network. Normalization layer is use to normalize the output from the the previous layer. Dropout layer is to cut out the unwanted feature from the final vector.

4. Results and Discussion

4.1. Dataset

This project used a publicly available dataset [12]. It consist of contactless and corresponding contact-based fingerprints from 336 fingers. Total it has 4032 images. All the images in this set are not suitable for the training, due to the imperfection in the ridges. So some of them are manually deleted and remaining are used for training and testing. 33 percentage of total images are used for the testing. Here each images are also resized into (192*192).

4.2. Performance Evaluation

The proposed system is implemented on Intel(R) Core(TM) i3-4005U 1.70GHz CPU with 4GB RAM. The training is done in 10 epochs. The time taken for each epoch are listed in the tables. It also include loss and accuracy of training and validation on each model. Each subnets are listed in different tables to clearly understand. From this tables it is clear that, the accuracy is increasing epoch by epoch.

Table 1. Performance of Sub-net1

Epoch	time	Training loss	Training accuracy	Validation loss	Validation accuracy
1	314s	0.2173	0.9157	0.3754	0.9478
2	181s	0.0022	1.0000	0.1410	1.0000
3	176s	7.8617e-04	1.0000	0.1780	0.9714
4	175s	4.0459e-04	1.0000	0.1846	0.9604
5	178s	1.6983e-04	1.0000	0.1051	0.9806
6	179s	1.3244e-04	1.0000	0.0461	0.9899
7	184s	1.4970e-04	1.0000	0.0152	0.9966
8	194s	8.2717e-05	1.0000	0.0048	0.9992
9	188s	6.2696e-05	1.0000	0.0013	1.0000
10	189s	5.1994e-05	1.0000	3.5719e-04	1.0000

Table 2. Performance of Sub-net2

Epoch	time	Training loss	Training accuracy	Validation loss	Validation accuracy
1	99s	0.3235	0.8987	0.7405	0.5497
2	97s	0.0487	0.9813	0.7747	0.5497
3	97s	0.0274	0.9925	0.8529	0.5497
4	99s	0.0152	0.9942	0.9589	0.5497
5	99s	0.0192	0.0192	0.8981	0.5497
6	101s	0.0121	0.9958	0.7769	0.5497
7	102s	0.0078	0.9971	0.5131	0.9596
8	101s	0.0194	0.9950	0.7904	0.4503
9	102s	0.0091	0.9967	0.8506	0.4503
10	100s	0.0076	0.9979	0.9371	0.4503

Table 3. Table Label

Epoch	time	Training loss	Training accuracy	Validation loss	Validation accuracy
1	101s	0.6929	0.5230	0.6919	0.5497
2	97s	0.6925	0.5230	0.6910	0.5497
3	98s	0.6923	0.5230	0.6906	0.5497
4	98s	0.6922	0.5230	0.6904	0.5497
5	99s	0.6922	0.5230	0.6900	0.5497
6	100s	0.6921	0.5230	0.6900	0.5497
7	100s	0.6922	0.5230	0.6897	0.5497
8	97s	0.6921	0.5230	0.6899	0.5497
9	97s	0.6921	0.5230	0.6896	0.5497
10	97s	0.6921	0.5230	0.6895	0.5497

This model gives 66.67% accuracy in publicly available fingerprint dataset [12]. In case of existing model [1] authors used an old minutiae extraction method [11]. The cross number method for the minutiae extraction reduce the total time to learn the subnetworks. It helps to improve the performance of overall system.

5. Conclusion

Fingerprint cross matching is a challenging problem. Several studies are conducted to efficiently solve this problem. But cross comparison of 2D contact based and 2D contactless fingerprints still becomes a challenge. This work proposes a CNN based model to effectively match 2D contactless and contact based fingerprints. Minutia features and ridge features are extracted separately from images. These features along with the original fingerprint image is given to a CNN separately. The individual results are combined at the end to produce the matching score. The proposed model gives better performs in fingerprint cross matching.

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