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Contactless Fingerprint Recognition System Based On CNN

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Abstract

Fingerprint recognition is a popular problem in the field of pattern recognition. It is majorly used in modern authentication technology like in access devices in mobile phones. The goal of this project is to investigate the applicability of convolutional neural networks for fingerprint recognition. This paper builds a CNN-based framework to precisely match contactless and contact-based fingerprint images. This framework initially trains a multi-Siamese CNN using fingerprint details, respective ridge map and specific area of ridge map. A distance-aware loss function is generated using deep fingerprint representation. For more accurate cross comparison deep fingerprint representations generated in such multi-Siamese network are concatenated. The proposed methodology for cross-fingerprint comparison is calculated on two publicly available data. The available database contains contactless 2D fingerprints and respective contact-based fingerprints.

Keywords*- CNN,Neural network, SVM,Dataset, RELU,Convolution,GPU*

I. INTRODUCTION

These days fingerprint verification systems are popularly used in personal identification and verification systems. Nowadays, fingerprint recognition has been accepted officially for personal identification. The security departments identify the criminals by using the fingerprints left on the suitable surfaces. There are several methods introduced for fingerprint recognition in the literatures. The first paradigm of the Cellular Neural Networks (CNN) is introduced by Chua and Yang.

The structure of CNN is simple and parallel that makes it suitable for image processing. The CNN architecture contains many processing cells. The cells operate in parallel in a 2D grid. Each cell is connected to the cells in its local neighborhood only. The CNN cells are really simple circuit nodes. Hence many of them can easily be integrated into a single chip. Consider an image of 64x64 pixels to be processed. Then a 64x64 CNN cells can be used to process the image by using a series of CNN algorithms. That means each pixel corresponds to each cell in the CNN. The faster processing is provided by the built in parallelism. The structure of the CNN is simple and because of its simple structure it is suitable for VLSI implementation. Different image processing tasks, such as edge detection, noise removal, contrast stretching, dilation and erosion can be performed by changing the template coefficients of the CNN

II. RELATED WORK

Almost to the mark comparison of contactless 2D fingerprint images with contact-based fingerprints is difficult for the success of emerging contactless 2D fingerprint innovations, which offer more clean and deformation-less acquisition of fingerprint features. Convolutional neural networks (CNN) have proved its remarkable capabilities in biometrics recognition. However, there have been almost no attempts to match fingerprint images using CNN based reaches.

Paper [1] develops a CNN-based framework to accurately match the contactless and contact-based fingerprint images. Our framework first trains a multi-Siamese CNN using fingerprint, respective ridge map and specific region of ridge map. This network is used to produce a deep fingerprint representation using a distance-awareness loss function. Deep fingerprint representations generated in such multi-Siamese network are concatenated for more accurate cross comparison. The proposed approach for cross-fingerprint comparison is evaluated by two publicly available databases containing contactless 2D fingerprints and respective contact-based fingerprints. Our experiments are presented in this paper consistently achieve outstanding results, over various popular deep learning architectures and over contactless to contact-based fingerprints comparison methods in the literature.

Paper [2] presents a Cellular Neural Networks (CNN) based rotating invariant fingerprint recognition system by taking in consideration the hardware implements ability in mind. Core point was used as a origin point and detection of the core point was implemented in the CNN framework. Developed system consists of four stages: pre-processing, feature extraction, false feature elimination and matching. Preprocessing enhances the input fingerprint image. Feature extraction creates rotation invariant features by using core point as a preface point. Unmatched feature elimination increases the system performance by removing the false minute points. Matching stage compares extracted features and produces a matching score. Recognition performance of the proposed system has been tested by using high resolution Poly U HRF DBII databases. The results are very helpful for implementing a CNN based fully automatic rotation invariant fingerprint recognition system.

paper [3] present a fingerprint PAD scheme based on i) a newly captured device able to acquire images within the short wave infrared (SWIR) spectrum, and ii) an in-depth analysis of various state-of-the-art techniques based on both handcrafted as well as deep learning features. The approach is evaluated on a database comprising over 4700 samples, stemming from 562 different subjects and 35 different presentation attack instrument (PAI) species in them. The results show the soundness of the successful approach with a detection equivalent to error rate (D-EER) as low as 1.36% even in a realistic scenario where five different PAI species are considered only for testing purposes (i.e., unknown attacks).

In [4], author investigated all the possibilities of incorporating artificial neural networks into the fingerprint identification process, implemented and documented our own software solution for fingerprint identification based on neural networks whose impact would mainly affect on feature extraction accuracy and overall recognition rate was highly evaluated. The result of this research is a fully functional software system for fingerprint recognition that consists of fingerprint sensing modules by using high resolution sensor, image enhancement module responsible for image quality restoration, Level-1 along with Level-2 feature extraction module based on neural networks, and finally fingerprint matching module using the industry standards BOZORTH3 matching algorithm. Aim of evaluation we used more fingerprint databases with differing image quality, and the performance of our system was evaluated using FMR/FNMR and ROC indicators. From the obtained results, we may come to conclusions about a very significant impact of neural networks on overall recognition rate, specifically in bad quality.

In paper [5], a fully Cellular Neural Networks (CNN) based fingerprint recognition system is introduced. The system includes a preprocessed phase where the input fingerprint image is developed and a recognition phase where the enhanced fingerprint image is matched with the fingerprints in the pre-defined database. Both preprocessing and recognition phases are realized by means of CNN approaches. A novel application of skeletonization method is used to perform ridgeline thinning which improves the quality of the extracted lines for other upcoming processing, and hence increases the overall system performance.

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III. PRPPOSED METHEDOLOGY

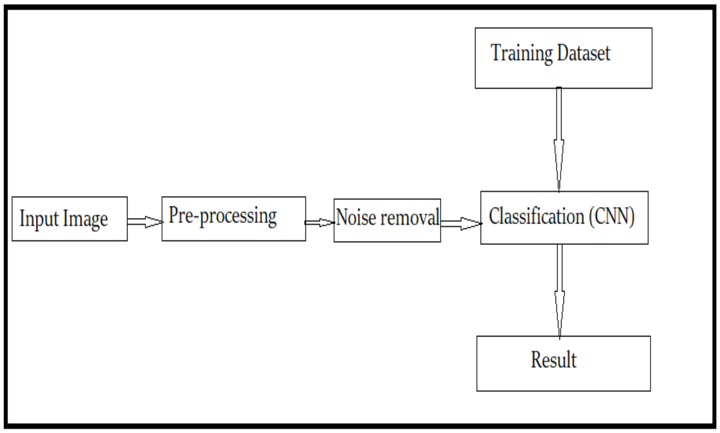


Fig. 1. Block Diagram of Proposed System

A. Image Enhancement:

The results of pre-processed image are highly enhanced by automotive and accurate classification of the image. The image enhancement technique is divided into two parts which are spatial domain technique and frequency domain innovation. In spatial domain technique the value of the pixel is exchanged with respect to the requirement while the frequency domain technique deals with the rate of change of the image pixels which are changing due to spatial domain. It cannot be determined that what type of technique is better for image enhancement. There are various techniques are used for image enhancement.

B. De-noising Method:

A essential step in image processing is the step of removal of various kinds of noisy elements from the image. In this stage, various de-noising methods will be used to get good quality of the image by removing the unnecessary noise from the MRI image. The important property of a good image de-noising model is that it should completely remove noise as far as possible as well as preserve edges. The image de-noising technique will be mainly depending upon the type of the image and noise in cooperating with it. There have been various published algorithms and each approach has its assumptions, advantages, and limitations. Spatial filters like mean and median filter are useful to remove the noise from image.

C. Feature Extraction:

The last stage includes feature extraction from the image. Image feature extraction is one of the most important techniques of image processing. It uses different techniques and algorithm to bifurcate and detect various shapes and portions of the image. There are numerously introduced techniques to apply this to the image. Wavelet transform is one of the tool for feature extraction. The wavelet transform has a characteristic of analyzation of the image with varying unit of resolution and has multi resolution analytic property. The wavelet transform is better than Fourier transform and a short time Fourier transform because preserves both time and frequency as in Fourier transform.

One of the main part of neural network is convolution network(CNN). CNNS use image recognition and classification in order to detect objects, recognize faces, etc. They are made up of neurons with learnable weight.

Each specific neuron receive numerous inputs and then takes a weighted sum over them, where it passes it through an activation function and respond back with an output.

IV. ALGORITHMS

Convolutional Neural networks CNN are well designed to process data through multiple layers of arrays. This type of neural networks is used in applications like image recognition or face recognition. The main difference between CNN and any other ordinary neural network is that CNN takes input as a 2D array and operates directly on the images rather than focusing on feature extraction which other neural networks puts light on. In the past years almost all state-of-the-art algorithms in the field of image recognition are based on the Convolutional Neural Networks (CNN). The idea of CNNs was presented in the early 80s but there wasn't enough for the computational resources to train an efficient network for image processing that times. Nowadays with a power of Global Positioning Unit computing, deep research on theoretical investigations and more training data CNNs have become demanding. CNN is a Feed-forward Neural Network where each neuron is responsible for a region, where regions could overlap with each other. A biggest advantage of CNN is that it requires very small image pre-processing and it learns which feature to be found in the image during the process of training while in other algorithms of image classification features are hand-engineered. CNN consists of the input layer, the output layer and multiple hidden layers, such as convolutional, pooling, fully interconnected layers and normalization.

The dominant approach of CNN involves solutions for questions of recognition. Top companies like Google and Facebook have done many research and development towards recognition projects to get activities done with greater speed.

A convolutional neural network uses three basic ideas −

- Local respective fields
- Convolution
- Activation layer
- Pooling
- Fully connected layer

CNN uses spatial correlations that exist within the input data. Each concurrent layer of a neural network connects some input neurons. This specific region is called local receptive field. Local receptive field focusses on the hidden neurons. The hidden neurons process the input data inside the mentioned field not realizing the changes outside the specific boundary.

CNNs have same performance to the ordinary fully connected Neural Networks. These convolutional networks have weights that can learn from the input and biases. Every neuron connected in the network receives an input and performs a dot product on it. This proceeds in not a linear fashion. There is a single differentiable score function at last. This function consists of scores that we obtain from the various layers of the neural network. Finally, a loss function at the end to evaluate the performance of the model. The convolutional neural network is different from the standard Neural Network in the sense that there is an explicit assumption of input as an image.

This consideration helps the architecture to definition in a more practical manner. For example, unlike the linear arrangement of neurons in a simple neural network. These neurons have an overall structure of three dimensions – Length, Width, and Height. For instance, images in the CIFAR 10 dataset will contain images of dimensions 32x32x3 and the final output will have a singular vector of the images of dimensions 1x1x10. The architecture of the Convolutional Neural Network is as follows –

Convolutional layer :

The first layer in a CNN network is the convoluion layer, which is the core building block and does most of the computational heavy lifting. Data or imaged is convolved using filters . Filters are small units that we apply across the data through a sliding window.the depth of the image is the same as the input for a color image that RGB value of depth 4 would also be applied to it. The convolutional layer is a building block of CNN. It does the most massive computational work. To be named a Convolutional Neural Network, the neural network must have at least one convolutional layer. Its main advantage is CNN learns to detect necessary features by itself. And other advantage is it doesn't require any intervention in feature engineering. We can draw an analogy between how our brain makes its image processing and how convolutional layers learn their filters. This process involves taking the elementwise product of filters in the image and then summing those specific values for every sliding action. The output of convolution that has a 3d filter with color would be a 2d matrix.

Activation layer:

Second is the activation layer which applies the ReLU(Rectified liner unit), in this step we apply the rectifier functions to increase nonlinearity in the CNN. Images are made of different objects that are not linear to each other.

Pooling layer:

Third is the pooling layer,which invloves down sampling of features. It is applied through every layer in the 3d volume .typically there are hypreparameters within this layer. The number of parameters is reduced by adding pooling layers. It is one more way to reduce the number of parameters. Its work is to reduce the size of the input volume. Pooling layers reduces the computational cost of training. It control the overfitting problem. Pooling operation is a form of non-linear down-sampling. It applies to every depth slice separately as to two-dimensional matrix. Each input to a pooling layer is divided into non-overlapping regions. Then one number represent each of these regions in the next stages.

Fully connected layer

Fully connected layer, which involves flattring. This involves transforming the entire pooled feature map matrix into a single column which is the fed to the neural network for processing. With fully connected layers, we combined these features together to create a model. Finally, we have an activation functions such as softmax to classify the output.

Each input image will pass it through series of convolution layers with filters. There is a convolution layer, activation layer, polling laye and fully connected layer, these are all interconnected so that CNNS can process data in order to classify images.

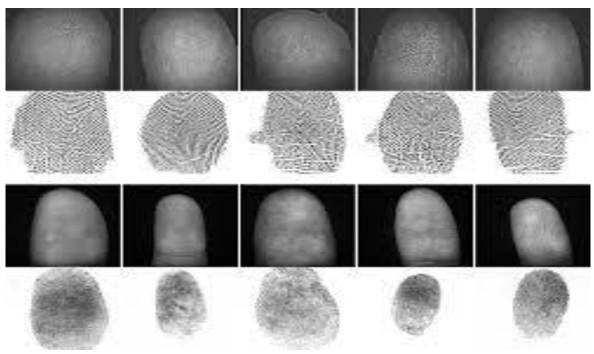
V. Expected Output

We proposed a CNN based system to match contactless fingerprints to contact based fingerprints. The system is capable of fingerprint sensing , feature extraction ,matching and image enhancement. This system consists of two phases. First phase is preprocessing phase and the second phase is recognition phase. The input fingerprint image is enhanced in preprocessing phase. In recognition phase the enhanced image is matched with the fingerprint in the database. Neural network take the data and push the data into layers. The learning process takes place in layers. Optimizer improves the learning process by updating knowledge in the network. In this way contactless fingerprints are matched with contact based fingerprints

(A) (B) (C)

Input image **Ridgeline thinning** **skeletonization method**

We take input image as shown in Fig (A) then preprocessing is done on that input image like ridegline thinning which is shown in Fig (B) after that skeleonization method isapplied on preprocessing image, Skeletonizatinon method is used to perform the ridgeling thinning. It improves the quality of the extracted lines and overall system performance., result of skleltonization method is as shown in Fig(C) and then by using CNN we can recognise image.



(D)

Fig (D) shows Contactless fingerprint and respective preprocessed contactless fingerprint from dataset.

VI. CONCLUSION

In this paper, we have presented a specially designed fingerprint cross comparison framework. It is used to accurately match contactless to contact-based fingerprints. This is the first such attempt to address challenging cross-fingerprint comparison problem using convolution neural network. The cross comparison using contact-based to contactless fingerprints are more challenging so it can be handled using this system very effectively. In practice, lack of sufficient training data, i.e. contact-based and respective contactless fingerprints, in proposed framework can significantly degrade the matching accuracy.

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