Finger vein recognition based on Deep Convolutional Neural Networks

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Abstract—**In the process of a finger vein image acquisition, finger vein images are susceptible to external factors like finger posture and light source conditions, which will result in poor recognition accuracy. Therefore, a finger vein recognition method based on improved convolution neural net work is proposed to improve the accuracy and robustness of the image recognition. Firstly, the collected finger vein image is preprocessed by image segmentation, finger root key point location and image extraction in the region of interest (ROI). Secondly, according to the application context of finger vein recognition, the convolution neural network structure is adjusted appropriately, and the output of convolution layer is standardized in batches. The optimized neural network is used to automatically extract, classify and identify the features of the preprocessed images. A large number of experiments were performed on public finger print data sets of Shandong University. The optimal recognition rates are 90% respectively. The experiments verify the effectiveness of this method.**

Keywords-component; finger vein recognition; ROI; convolution neural network; image feature extraction

I. Introduction

With the development of society and economy, traditional identification methods based on characteristic items (such as ID card, key, etc.) and specific knowledge (such as user name and password, U shield, IC card, etc.) are facing challenges. Especially in today's modern society, people have higher requirements for the reliability and security of identity authentication technology. Biometrics provides an effective and reliable solution in the field of identity identification based on one or more body features of a person (such as face, fingerprint, iris, vein, DNA, etc.) and behavioral characteristics (such as handwriting, gait, voice print, etc.) .[1] Finger vein recognition is to identify the veins hidden under the epidermis of human finger. Biometric recognition based on finger vein has a broad application prospect and has been widely concerned by relevant researchers. In recent years, the Deep Convolutional Neural Networks (DCONVOLUTIONAL NEURAL NETWORK) has been widely used in computer vision. Being different from manual extraction of finger vein image features and machine learning algorithm for recognition, DCCN does not have to extract image feature information manually, but can learn appropriate network parameters from a large number of training samples. After training the CONVOLUTIONAL NEURAL NETWORK, it can be used to extract the deep feature information of the input image and classify and recognize it. Through experiments on the datum set, the method is proved to be effective and robust. Recently, some people[12] began to apply the deep learning method in the field of finger vein recognition. The literature[11] proposed an algorithm to extract and repair finger vein veins by CONVOLUTIONAL NEURAL NETWORK, but the traditional algorithm was still used in the matching stage in the literature, which did not make full use of CONVOLUTIONAL NEURAL NETWORK's powerful feature extraction ability. In general, there are few researches and applications of deep learning in the field of finger vein recognition, a large part of which is due to the fact that the data set in the field of vein recognition is too small to support the training of deep neural network. Therefore, how to make full use of the current limited digital vein data set and design a reasonable deep neural network framework to extract the digital vein image features with strong discrimination ability is still a research difficulty at present. In addition, in order to obtain strong expression power, deep neural network usually has deep depth and large number of references, which makes its application in embedded devices more difficult. This is another difficulty in the application of deep learning in the field of finger vein recognition. Solving these two problems will promote the application and development of deep learning in the field of finger vein recognition.

II. Finger vein image preprocessing

Due to the influence of finger position, light conditions and other factors, the quality of the original finger vein images is different, so the original images need to be pre-processed in order to facilitate subsequent feature extraction and recognition. Miuura et al .[4] randomly initialized a batch of points in the digital vein image, and then obtained the digital vein veins in the whole image through repeated line tracking. This method can obtain the skeleton of the digital vein veins more accurately, but the algorithm itself needs repeated iteration, which is time-consuming. Liu et al .[5] improved the original repeated line tracking method to improve the robustness and efficiency of the original method. Compared with the image background, the gray value of the finger vein veins is lower, so the curvature of the cross section of the finger vein veins is larger. Based on this feature, Miuura et al .[6]

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obtained the finger vein veins by detecting the local maximum curvature value. Inspired by this, Song et al .[7] proposed the mean curvature method for extracting the veins of finger veins, and the robustness was improved to a certain extent. Qin et al .[8] Use regional growth operator to obtain finger veins, which has a good effect, but there is a very time-consuming problem. Yang et al .[9] first used the eight-direction Gabor filter to obtain the veins information in the digital vein images, and then used the reconstruction algorithm to fuse and derive the veins images. Zhang et al .[10] used curve waves to enhance the original digital vein images at multiple scales, and then designed a neural network with local interconnection structure to extract digital static.The central region of the finger gathers most of the effective features of the finger vein image, which is the Region of I nterest (ROI) of the finger vein image. ROI extraction scheme includes several stages of finger image segmentation, key point positioning and ROI extraction, specifically including image clipping, Gaussian smoothing filtering, finger segmentation, contour extraction, key point positioning, direction correction, ROI extraction and other steps, as shown in the figure[1].

A. *Extract peak ROI*

For the finger vein, the joint part of the vein is more of a concern because it carries more information. So it is necessary to find two joints on the midline. It can be seen from the figure that the image is converted to gray value. The area with higher gray value is what we need to study more, so we find the two joints through circulation.

B. *Gaussian smoothing filter*

For unavoidable noise, it will cause one peak next to another peak. In fact, it is not the peak obtained by two joints but caused by noise. The use of filter can effectively reduce the loss caused by noise.

C. *An extract of the original image*

After the two peaks are found, 20 pixels above and below the midline and 20 pixels around the peak are used to intercept the two ROI.

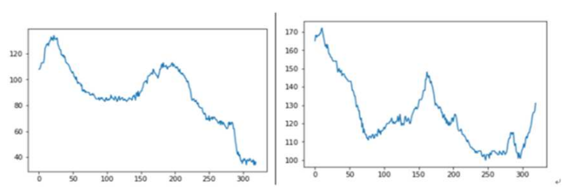

Figure1. The gray value of the image at the median

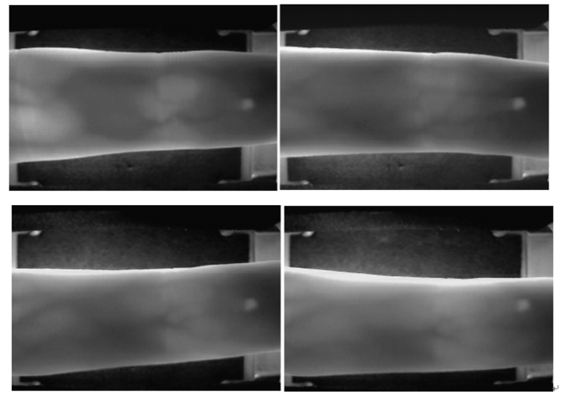

Figure2. The original image

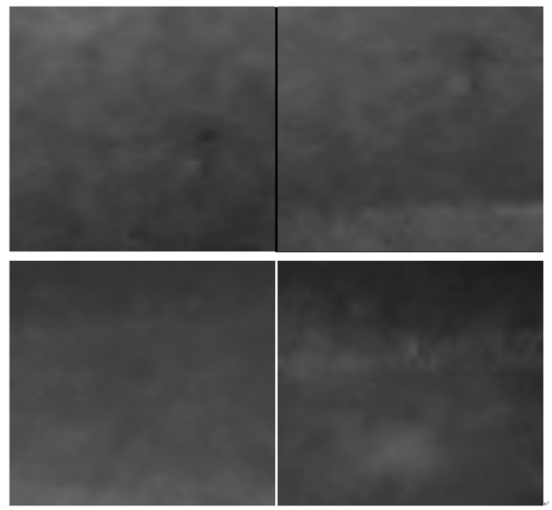

Figure3. The cropped image

III. DEEP CONVOLUTIONAL NEURAL NETWORKS

Artificial Neural Network (ANN) builds a mathematical model according to the operating principle of the Neural Network in human brain, and USES the weighted directed graph to connect the adjacent neurons, and then realizes the operation of the directed gragh ,[13,14] through hardware or software. In other words, artificial neural network is a mathematical model for the relationship between neurons, input and output. At present, Hopfield network, BP network, Boltzmann machine, SOFM network and ART network are widely used. The concept of perceptron is derived from biological nerve cells and is a simple abstraction of its description. Nerve cells are mainly composed of dendrites, synapses, axons and cell bodies.[15,16] The nerve cell has both "activated" and "inactive" states. When a nerve cell inputs an activation signal to the cell, the nerve cell changes state in response to prominent inhibition or reinforcement. When the intensity of the signal received by the neuron reaches a threshold, the cell produces an electrical impulse. The pulse travels through the axon to the next neuron. The concept of perceptron, in which the weight value represents prominent and the activation function represents the cell body, is proposed based on the operation mechanism of neurons.

The most common form of machine learning, deep or not, is supervised learning. Imagine that we want to build a system that can classify images of different people's finger vein. We first collect a large data set of images of finger vein each labelled with its category. During training, the machine is shown an image and produces an output in the form of a vector of scores, one for each category. We want the desired category to have the highest score of all categories, but this is unlikely to happen before training. We compute an objective function that measures the error (or distance) between the output scores and the desired pattern of scores. The machine then modifies its internal adjustable parameters to reduce this error. These adjustable parameters, often called weights, are real numbers that can be seen as ‘knobs’ that define the input–output function of the machine. In a typical deep-learning system, there may be hundreds of millions of these adjustable weights, and hundreds of millions of labeled examples with which to train the machine[2].

The small NN is widely used in the early 90s', which were shallower or had fewer maps per layer compared with DNN. DNN have hundreds of maps per layer, inspired by Noecognitron, with 6-10 layers of non-linear neurons stacked on top of each other, comparable to the number of layers found between retina and visual cortex of macaque monkeys. Obviously, DNN have a better accuracy. It was a pity that the hardware in that time made this idea unattainable. However, hardware is no longer the obstacle. Today's computers, however, are fast enough for this, more than 60000 times faster than those of the early 90s'[3].

In machine learning, convolutional neural network is a kind of deep feed forward artificial neural network, which has been successfully applied to image recognition. Artificial neurons can respond to surrounding units and perform large-scale image processing. A convolutional neural network consists of a convolutional layer and a pooling layer. The ReLU function and Softmax function are used as activation functions in the convolutional layer. The ReLU function is introduced to solve the gradient dispersion problem when the neural network is deep.

The ReLU function is expressed as:

$$f(x) = \begin{cases} 0, & x \le 0 \\ x, & x > 0 \end{cases}$$

For image recognition, feature extraction is the most important step. Therefore, the network structure of this paper is made up of the combination of the convolutional neural network and the deep neural network, which are better in the field of image recognition.

When it comes to the architecture of the network, several classic networks are well-known like LeNet-5, AlexNet, and ZfNet.

LeNet5 is a convolutional neural network designed by Yann LeCun for handwritten numeral recognition in 1998. At that time, most Banks in the United States used it to recognize the handwritten numeral on checks. It is one of the most representative experimental systems in the early convolutional neural network. The convolutional neural network is able to derive an effective representation of the original image, which enables it to identify the visual regularities above directly from the original pixel with minimal preprocessing. However, due to the lack of large-scale training data at that time, the computational ability of the computer could not keep up with it. Lenet-5 was not ideal for the processing of complex problems.

Since 2006, many methods have been designed to overcome the difficulty in training deep convolutional neural networks. Among them, the most famous one is a classical network structure proposed by Krizhevsky, which has made a great breakthrough in image recognition task. The overall framework for its approach, called AlexNet, is similar to Lenet-5, but a little deeper.

AlexNet neural network is one of the foundations of deep learning, which was proposed by Hinton and his student Alex krizhevsky in 2012. Its main structure is 8 layers deep neural network, including 5 layers convolutional layer and 3 layers all-connected layer (activation layer and pool layer not included).

Unlike Alex Net, which uses a sparse architecture of two GPUs, ZfNet uses only one GPU with a dense connection structure. At the same time, the first layer of ZfNet uses smaller convolution cores and convolution steps, thus retaining more features. As the network deepens, more distinguishing features can be learnt. When the light or the environment is not ideal, ZfNet can performed better in finding out the key parts of the image, so this paper adopts ZfNet structure.

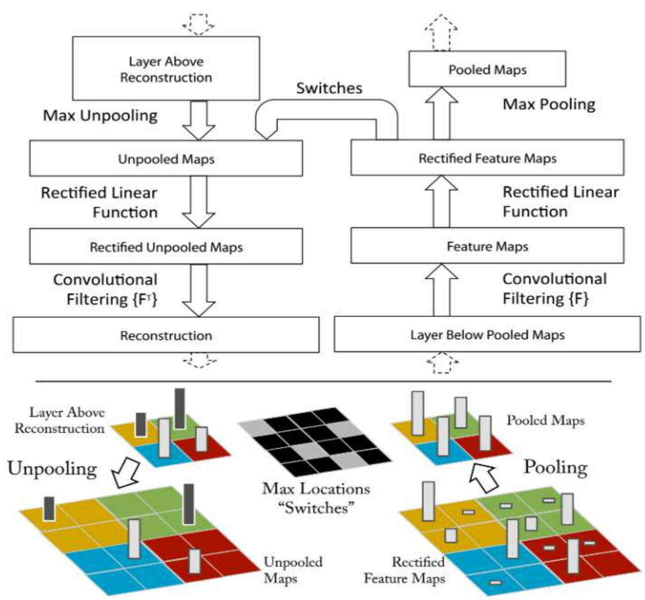

Figure4. Top: A deconvnet layer attached to a convnet layer. The deconvnet will reconstruct an approximate version of the convnet features from the layer beneath. Bottom: An illustration of the unpooling operation in the deconvnet, using switches which record the location of the local max in each pooling region during pooling in the convent.

IV. THE EXPERIMENT

A. The data set

The finger veins of 106 subjects (12 pictures of index finger, middle finger and ring finger respectively) were collected from the database of Shandong University. The data set includes finger images under four different wavelengths of light: red, green, blue and near-infrared, in which finger-vein images are taken under near-infrared light.

B. The evaluation index

In this paper, accuracy (Acc) and Loss Function (Loss) are selected to measure the accuracy and robustness of the model respectively. The loss function USES the cross entropy loss function.

The formula for calculating the accuracy rate is as follows:

$$Acc=\frac{TR}{TR+FA}$$

TR (True) and FA (False) are the number of samples correctly classified, number of samples incorrectly classified respectively.

The formula for calculating the accuracy rate is as follows:

$$Loss=-\frac{1}{N}\sum_{i=0}^{N-1}\sum_{k=0}^{k-1}y_{i,k}\log p_{i,k}$$

K is the number of classes in a multi class task; N is the number of samples; y is the true class of the samples; $p_{i,k}$ is the First Class; $y_{i,k}$ is the probability of the Class K;

C. Experimental environment

The experimental equipment is an Intel core i7 processor, NVIDIA1060 graphics card, 16 GB of memory system, operating system for windows10 server. The programming language used was Python3.7, with BatchSize set to 64 and a total of 150 epochs trained.

D. Experimental results and analysis

Finger vein image taken under near infrared light in palmprint library. Among them, there are 600 images in the training set and 600 images in the test set. All images are preprocessed and normalized to 128×128 size after the ROI region is extracted, which is then used as the input of the neural network. The experiment was carried out under the experimental environment and parameters, and the experimental results were unexpectedly good with 86 percent accuracy and the loss is 0.9 approximately.

V. REFERENCES

[1] Kun Ling; Yingjie Lei; "Research on palm vein recognition algorithm based on improved AlexNet convolution neural network". Modern electronic technology, 2020 (7) : 43-56.

[2] Yann Lecun; Yoshua Bengio; Geoffrey Hinton; "Deep learning". Nature, 28 MAY 2015: 436-444.

[3] Ciresan, Dan; Meier, Ueli; Schmidhuber, Jürgen, "Multi-column deep neural networks for image classification," 2012 IEEE Conference on Computer Vision and Pattern Recognition, pp. 3642–3649.

[4] Miura N.; Nagasaka A.; Miyatake T. "Feature extraction of finger-vein patterns based on repeated line tracking and its application to personal identification". Machine Vision and Applications,2004,15(4):194-203

[5] Liu T.; Xie J.; B.Yan; W.,et al. "An algorithm for finger-vein segmentation based on modified repeated line tracking"The Imaging Science Journal, 2013,61(6):491-502

[6] Miura N.; Nagasaka A.; Miyatake T. "Extraction of Finger-Vein Patterns Using Maximum Curvature Points in Image Profiles" IEICE Transactions on Information and Systems，2007,90(8):1185-1194

[7] Song W. Kim T.; Kim H.C.et al. "A finger-vein verification system using mean Curvature" Pattern Recognition Letters，2011,32(11):1541-1547

[8] Qin H.; Qin L.; Yu C. "Region growth-based feature extraction method for finger-vein Recognition" Optical Engineering,2011,50(5):572081-572088

[9] Yang J.; Yang J.; Shi Y. Finger-vein segmentation based on multi-channel even-symmetric Gabor filters IEEE International Conference on Intelligent Computing and Intelligent Systems 2009:500-503

[10] Zhang Z; Ma S.; Han X. "Multiscale Feature Extraction of Finger-Vein Patterns Basedon Curvelets and Local Interconnection Structure Neural Network" 18th International Conference on Pattern Recognition 2006:145-148

[11] Qin H; EI-Yacoubi M A. "Deep Representation -Based Feature Extraction and Recovering for Finger-Vein Verification" IEEE Transactions on Information Forensics and Security, 2017, 12(8): 1816-1829

[12] Wu chao; Shao xi;"Study on finger vein recognition based on deep learning" Computer Technology and Development, 2018, V. 28; No.250(02):206-210.

[13] Koprinkova-Hristova P, Mladenov V, Kasabov N K. Artificial Neural Networks[J]. Europe an Urology, 2015, volume 40(I):245.

[14] Yao X. "Evolving artificial neural networks" Proceedings of the IEEE, 1999, 87(9):1 423-1447. .IEEE, 1995, 84(6):906.

[15] Chen En wei; Wang Yong; Lu Yimin, et al. "Research on the Linear Classification Method based on perceptron Neural Network" Chinese Process Control Conference.2008.

[16] Ketkar N. Convolutional; "Neural Networks/ Deep Learning with Python" Apress, 2017.