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A Convolutional Neural Network Method for Palm Vein Recognition

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ABSTRACT *In recent years, identity authentication by using biometric features has received more and more attention. Unlike the traditional finger print recognition, the blood vein image lies under the skin and is difficult to forge. Therefore, identity authentication by employing blood vein image is with higher security than using finger print. In this study, we have proposed a method, which is based on convolutional neural network and aims at recognizing the identity of certain palm vein images. The convolutional neural network was proved to achieve good performance in image recognition tasks. Comprehensive experiments have demonstrated that the proposed method achieves high success rates in identity authentication and should have a wide range of applications*

KEYWORDS : Image recognition, Palm vein image, Convolutional neural network

INTRODUCTION

In recent years, identity authentication by using biometric features has received more and more attention. More specifically, the biometric features extracted from human hands, i.e., palm print or palm vein print, are extensively employed in identity authentication. Unlike the finger print, which contains very limited information and is easily forged, the palm vein print is not a simple image and the image pattern is hidden under skin. The pattern of blood veins is unique to every individual, even among identical twins. Furthermore, the pattern of blood veins does not vary during the person's lifetime. This characteristic makes palm print recognition to achieve very high success rates. Besides, the blood vein pattern lies under the skin. Therefore, it cannot be easily forged and is with high security. On the other hand, convolutional neural network (CNN) has achieved good performance in image recognition tasks, i.e., face recognition and finger digit recognition. To this end, we propose a new method for identity authentication. The method takes palm vein print images as inputs and employs CNN algorithm for classification. Extensive experiments have demonstrated that the proposed method is very accurate in identity authentication.

METHODS

The proposed method consists of the following steps: generation of palm vein images, preliminary image processing, dynamic binarization process, median filtering, convolutional neural network training and image recognition, see Figure 1.

Generation of palm vein images

Based on the characteristic of human bone and muscle tissues, when the wavelength of light source is between 0. 72μm and 1. 10μm, the light can penetrate the bone and muscle tissues and generate the image of veins. The wavelength of the light belongs to the near-infrared ray. Therefore, we have set up a palm vein capture system based on near-infrared ray. The system includes a near-infrared ray camera, an adjustable infrared light source and a black box as shell

Preliminary image processing

The preliminary image process step contains two sub-steps:

1. Image compression. The raw images produced by the camera are with a resolution of 1280*960. While the CNN algorithm does not require images with such high resolution. Additionally, images with high resolution results in more computation time and requires more memory. To this end, the images are compressed for 100 times to a resolution of 128*96. Experiments have demonstrated that the compressed images have retained the structural information of palm veins and the image compression step has little impact

on the success rates of image recognition.

2. Intensity normalization. The images produced by the palm vein capture system depend on the illuminance and when and where the images are captured. Therefore, the images may have different gray scale distributions. The difference of gray scale distribution leads to inconsistence in feature extraction, sample training and image recognition. Therefore, we have performed intensity normalization on the images.

Dynamic binarization process

To acquire more information, we employ image enhancement technology to process the images produced by the last step. Previous studies have demonstrated that the laplace operator cannot capture the structural information of palm veins. In this study we employ the OSTU algorithm that dynamically performs binarization on the images. The algorithm divides the raw image into several sub-images and performs binarization on each of the sub-images. The threshold for binarization not only dependents on the gray values of the pixels of each sub-image, but also dependents on the location of the pixels. The method works as follows:

Denote *t* is the threshold to distinguish the foreground and background, the fraction of the pixels of the foreground is w_0, and the average gray value of the pixels of the foreground is u_0. The fraction of the pixels of the background is w_1, and the average gray value of the pixels of the background is u_1. Thus the average gray value of the full image is:

$$\mathrm{u} = w_0 * u_0 + w_1 * u_1$$

The variance between the background and foreground is：

$$\begin{aligned} \mathrm{g} = w_0 * (u_0 - u)^2 + w_1 * (u_1 - u)^2 \\ = w_0 * w_1 * (u_0 - u_1)^2 \end{aligned}$$

When the variance achieves its maximal value, the foreground and background achieve the largest variance. The threshold results in the largest variance is calculated as

$$\mathrm{sb} = w_1 * w_2 * (u_1 - u_0) * (u_0 - u_1)$$

Median filtering

Although the dynamic binarization process retains the structural information of the palm vein images, we note that the edge of the veins is rough and the images contain a number of isolated pixels. To this end, we employ the median filtering technique to process the images. The median filtering method is a non-linear method. It firstly sorts the gray values of the pixels with a sliding window. Subsequently, it uses the median value within a window to replace the pixel at the center of the window. The median filtering method retains the details of the image while the linear filtering method usually blurring the details of images.

Convolutional neural network training

The convolutional neural network (CNN) method is widely used in image recognition. In general, CNN is a type of feed-forward artificial neural network in which the connectivity pattern between its neurons is inspired by the organization of the animal visual cortex. However, CNN contains three distinguishing features when contrasted to the traditional multilayer perceptron models: 3D volumes of neurons, local connectivity and shared weights. These properties allow CNN to achieve better generalization on vision problems. The training of CNN mainly consists of two steps: the forward stage and the backward stage.

In the forward stage, the samples start from the input layer, the values transmitted layer by layer until the output layer. Firstly, take a sample (X, Y_p) from the image, where *X* is the input of the first layer. Then we perform convolution in the first layer. In the experiments, we set the size of the kernel as 5*5 and we employ 12 distinct kernels. The size of the input images is 128*96. After the first convolution process, we generate 12 images with a resolution of 124*92. The second layer is the pooling layer, which is another important concept of CNN. The size of the pooling window is set as 4*4 and we generate 12 images with a resolution of 31*23. In this way, a pooling layer always follows a convolution layer and the next convolution layer follows the previous pooling layer, we set up the architecture of the CNN.

In the backward stage, the error between the real output and the expected output is estimated:

$$E_p = \frac{1}{2}\sum_{j=1}^{m}(Y_{pj} - O_{pj})^2$$

where O_p is real output and Y_p is expected output. Assume E_p is the error arisen by the *p-th* sample, therefore the total error arisen by the training model is calculated as:

$$E = \sum E_p$$

Similar to back-propagation neural network, CNN adjusts its weights along the direction of the gradient of the weights

Image recognition

We employ the 10 fold cross validation method to assess the performance of our system. The data (palm images of each person) is equally divided into 10 subsets. Each round, we use 9 subsets for training the CNN model and the remaining subset to test the performance of the model. The test subset is shifted for 10 times so that each of the subset was used as test set for once. Eventually, the results of the 10 folds were averaged.

RESULTS AND DISCUSSION

We have captured the palm vein images of 3 different individuals. For each of the 3 individuals, 20 images were captured. In CNN training, the weights were adjusted for 500 times. We use error rate, sensitivity and specificity to assess the CNN model.

The results are given in Table 1. We note that the error rates of the 3 individuals vary between 0% and 9% and the average error rate is 4.7%. The sensitivities of the 3 individuals are between 0.9 and 1. The specificities of the 3 individuals are between 0.95 and 1. To summarize, the proposed method achieves high success rates in identity authentication.

Table 1. The error rate, sensitivity, specificity of the CNN model on 3 different individuals.

Individual ID	Error rate	Sensitivity	Specificity
Person A	2/22=9.09%	20/(20+0)=100%	38/(38+2)=95%
Person B	1/20=5%	19/(19+1)=95%	39/(39+1)=97.5%
Person C	0/18=0%	18/(18+2)=90%	40/(40+0)=100%
Total	4.70%	95%	97.5%

Figure1. Prediction accuracies of NaiveBayes, Kstar and DecisionStump algorithms on three distinct feature spaces: the original data space, the PCA feature space and the feature space generated by this method.

CONCLUSIONS

This study proposes a palm vein capture system and a CNN model for the recognition of the identity of the images. Comprehensive experiments demonstrate that the proposed method achieves high success rates in identity authentication and should have a wide range of applications

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