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Biometric Verification Pattern and Feature Extraction Model based on Convolution Neural Network

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Abstract: Biometric verification pattern and feature extraction is a hand based recognition system that is essentially based on human vein recognition method. It is a most emerging technique and its been gaining an increasing attention. In many cases because of weak contrast of normal light concentration in veins, the predicted finger vein images are quality wise degraded. Due to this issue the biometric model is often unreliable, and fades its accuracy of finger vein verification. Analyzing the most suitable ways we have proposed a simple and effective feature extraction model for biometric verification. We have used the various methodologies to recover the vein pattern with a clear vein region is extracted with gray scale and downstream techniques. This way recovers the ambiguous region with contrast and entropy factors before.

Keywords: Palm recognition, biometric verification, feature extraction, convolution neural network.

I. INTRODUCTION

A process of converting an image into digital object and at the same time applying some operations on it, so as to get the further enhanced image. In others word to extract some information from an image. It is an another types of signal exemption with the input as an image or video and output may be image or image characteristics [7], multi column deep neural network [8], and iris detection [9], spoofing detection[10] can threatened to verification system. user's knowledge. particularly, vein verification provides higher security and privacy for the user. Steps involved in processing an image:

Acquiring an image with the help of photography. Analyzing an acquired image, then manipulating it which involves compressing an image data, finding specific methodologies invisible to human eyes. The final step is the output result which is a modified image, entirely based on image analysis.



Fig. 1: Structure of vein in human palm and finger

II. RELATED WORK

In an existing system, the image is analyzed based on non adaptive technique, later a local interconnected network with a linear vein feature based on the centred patches. Further the network is instructed to find the linear sensory space of network and more rotation is done by some angle to collect the different linings of image. As an approach to detect the linear sensory space of neural network it suffers from inaccurate detection of finger image lines lowers the recognition accuracy of finger vein image.

M. A. Turk and A. P. Pentland [1] proposed that the front part of human head from forehead to chin is difficult. Visualizing the components in model and analyzing that model for that part is very tough process. This process presents a method for recognizing with the concept of theoretical model of information for programming and deprogramming for that particular part of an image.

J. Daugman [3] analyzed the working of human iris recognition. Algorithms developed for the purpose of identifying humans by totally depending on their iris eye patterns. It is been tested in most of the fields and trails in laboratories. This identifying principals to the failure of different tests performed for statistics impedance analyzing the iris structure, programmed by different wavelength.

A. Kumar and Y. Zhou [4] proposed a very new method to the performance improvement for person identification with vein verification method. This method intuitively gets the vein pattern and its lowest resolving printing images and mi all these proves with the help of some scoring-levels combinatorial novel strategies.

A. Krizhevsky, I. Sutskever, and G. E. Hinton [7], efficiently analyzed a huge, convolutional network to perform the proper classification of million fast resolving image in LSVRC-2010. Image net processing set to thousands of varying classes. While with the testing data, we can get highest from 1 to 5 bit results than the old state of results.

III. SYSTEM ARCHITECTURE

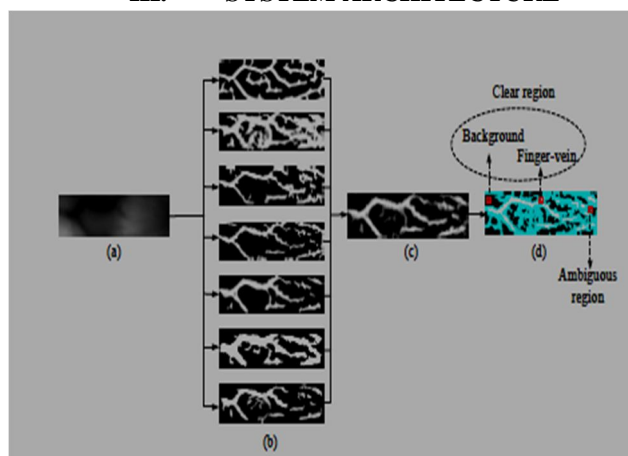


Fig2: labeling the vein pattern and its image pixels

- 1) An original image
- 2) Extracted vein features by using various theories.
- 3) Probability of mapping from the equation:

$$P(a, b) = \sum_{i=1}^I f_i(a, b) \div I \quad (1)$$

Where probability of each pixel (a, b) being finger vein feature, (i=1, 2, 3, ..., I=7)

- 4) An image with its pixels such as its most visible region, background and an ambiguous part.

$$L(a, b) = \begin{cases} 1 & \text{if } P(a, b) = 1 \\ 0 & \text{if } P(a, b) = 0 \end{cases} \quad (2)$$

We can assign L(a, b) of pixel (a, b) as given by equation (2). Acquiring an image. Preprocessing different enhancement techics on image for the best quality of source image. Methods includes:

Grayscale Image where an original form of red green blue additive pattern of image is transformed to grayscale pattern for more processing using the formula:

$$\text{grayImage} = \text{rgb2gray}(\text{rgbImage}) \quad (3)$$

Down sampling, the vein image was resized by the factor 0.5.

ROI Region Extraction, only vein region was taken by using binary mask generation and fractional dimension:

$$\text{frac_dim} = \text{FD}(\text{image}(\text{mask})) \quad (4)$$

Segmentation of vein pattern is performed. Repeating line tracking method is implemented for vein segmentation. After that thresholding method is used for binaries the segmented result and median filter is used for remove the noise in segmented result.

$$g(a, b) = \begin{cases} 1 & \text{if } P(a, b) > T \\ 0 & \text{if } P(a, b) \leq T \end{cases} \quad (5)$$

Where T is some range of intensity values. Feature extraction is carried out by local binary pattern. Finally mean, standard deviation, entropy, variance and contrast features are extracted. These features are our final feature vector.

$$\text{Mean } \mu = 1 / N \sum_{i=0}^{n-1} x_i \quad (6)$$

$$\text{Standard deviation } \sigma^2 = (1/N - 1) \sum_{i=0}^{n-1} (x_i - \mu)^2 \quad (7)$$

$$\text{Entropy} = - \sum_{i=0}^{n-1} p_i \log_b p_i \quad (8)$$

$$\text{Variance } \sigma^2 = (\sum X^2 / N) - \mu^2 \quad (9)$$

$$\text{Contrast} = \sum_{i,j=0}^{N-1} P_{ij} (i - j)^2 \quad (10)$$

Classifying the extracted feature, part of image using the KNN classifier to obtain the satisfactory results.

KNN classifier:

$$\hat{f}(x_q) \leftarrow \arg \max_{v \in V} \sum_{i=1}^k \delta(v, f(x)) \quad (11)$$

A. CNN Architecture

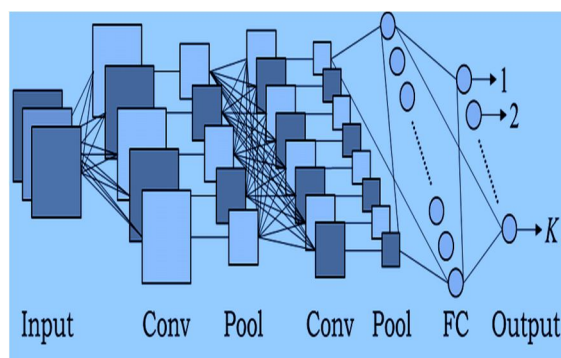


Fig 3: CNN Architecture

As shown in fig, consists of dual convolution layers which extracts the features, preceded by dual max pooling layers, future two normalization layers which are local, one of the fully connected layers and an output layer. Computes the two dimensional convolution with input mapping and a filter which extracts the features.

$$x_n^l = \max(0, \sum_m^{M^{L-1}} w_{n,m}^l * x_m^l + b_n^l) \quad (12)$$

x_m^l is the m-th input map of layer l. The n-th output map of layer l is computed by equation (3). Next we can use max pooling preceded by computing the output. As shown in Fig.3, Later for normalizing the local response is done by:

$$S_n^l(a,b) = A_n^l(a,b) / (\gamma + \alpha \sum_{n=\max(0,n-p/2)}^{\min(M,n+p/2)} A_n^l(a,b)^2)^\beta \quad (13)$$

Where $A_n^l(a,b)$ be the activity of output from convolutional layer by applying max pooling at position (a, b).

Further the final output layer is computed by the linear combination of inputs and outputs as:

$$o_n = \sum_{m=1}^M w_{n,m} * x_m + b_n \quad (14)$$

IV. ALGORITHM

Biometric verification pattern and feature extraction:

- 1) *Input:* Source palm vein image $f(a, b)$ and dataset Ω ;
- 2) *Output:* Enhanced image of vein pattern $F(a, b)$;
- a) *Step 1:* Collect extracted features of vein pattern based on 7 baselines and compute the probability map (as shown in Fig.2(c)).
- b) *Step 2:* Give a point label to every pixels in image by mapping the probabilities, take the patches which are in middle of the pixels as positive samples and patches centered on the background pixels as negative samples to form the training set A.
- c) *Step 3:* Train the network by stochastic gradient descent.
- d) *Step 4:* Input image $f(a, b)$ into network to obtain enhanced image $F(a, b)$.
- 3) *Return* $F(a, b)$;

V. RESULTS AND DISCUSSIONS

TABLE I Output from various numbers of layers

Methods	24(5*5)- 48(5*5)- 100	24(5*5)- 48(5*5)- 64(5*5)- 100	24(5*5)- 48(5*5)- 200-100
EER(%)	1.33	1.33	1.33
Time(sec)	2.58	3.45	3.77

Observing Table I, compared to the three-layers network, the cost of time increases significantly having similar accuracy on validation with other layers of network.

TABLE II Output from various kernel numbers

Methods	12(5*5)- 24(5*5)-50	24(5*5)- 48(5*5)-100	48(5*5)- 96(5*5)-200
EER (%)	2.67	1.33	1.33
Time(sec)	2.03	2.58	4.86

The outputs in Table II show that the methods first and third computation achieve the same EER. However, the basic network second reduces the time.

Observing fig 4, considering the database A and B with data partitioning, we can observe that the low EERs for A and B are achieved when the iteration steps are 3 and 2 respectively

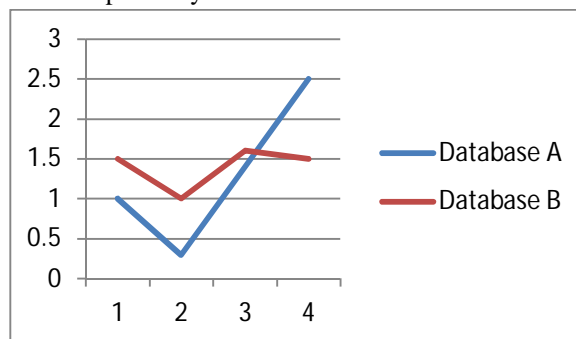


Fig 4: Iteration step (1, 2, 3, 4) varies with related EER on A and B

VI. CONCLUSION

The proposed system is a learning method for finger vein verification and also recovering for vein pattern. we have proposed a model for classification of vein pattern by using local binary pattern in the feature extraction method the mean, variance, standard deviation, contrast and entropy is calculated in response to the segmented vein pattern. Followed by the analyzed classes it is further recognized with the matched vein features. The recovering is carried out with the help of performance analysis by further improving the performance with high accuracy.

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