Soft Biometric Trait on Fingervein Recognition Using Cnnresnet

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Abstract- *Many finger vein feature extraction algorithms achieve adequate performance due to their ability to reflect texture, while simultaneously ignoring the finger tissue-forming intensity distribution and in some cases processing it as background noise. Use this kind of noise as a novel soft biometric feature in this project to achieve better output in finger vein recognition. First, a detailed analysis of the finger vein imaging theory and the image characteristics is provided to demonstrate that the intensity distribution produced in the background by the finger tissue can be extracted for identification as a soft biometric feature. Then, two finger vein background layer extraction algorithms and three soft biometric trait extraction algorithms are proposed for intensity distribution feature extraction. In the classification stage developed a system with implementation of convolution neural network specifically resnet18 for the training image dataset and image retrieving process is done. Purpose of introducing deep learning in developing finger vein identification system is to get accurate more performance and speedy results. Results are computed on the basis Euclidean distance between features obtained from test image and features of trained images, the model designed has good robustness in illumination and rotation.*

Keywords- soft biometric feature, resnet18, convolution neural network

I. INTRODUCTION

Biometric-based personal identification technology, e.g., fingerprint and face, receives more and more attention, as the security issue about personal information becomes increasingly important and relevant identification device becomes more affordable. Although very stable and accurate in recognition, biometric authentication technology will confront a common problem fraud or theft. For example, fingerprint acquired from an object surface or through violence could be used to spoof the fingerprint identification system. Similarly, the frontal face photo could be easily acquired from video, secret camera, and even facial plastic surgery.

For some civilian application, e.g., the identification system for a small company, this problem seems not critical. However, for the personal identification application in some sensitive places, e.g., bank, jail, and airport, need an effective way to reduce the risk caused by fake biometric as much as possible. Finger veins, which grow in a subcutaneous layer of the finger body, are a biometric hidden inside finger body, and thus naturally immune to fraud and theft. Therefore, in recent years, finger vein-based personal identification technology becomes a hot research topic, not only for its much lower recognition error than fingerprint and face but also more for its high security property. Proposed a finger vein-based personal identification system, where a near infrared (NIR) image of the finger vein is captured for identification.

Our finger vein-based personal identification system consists of three modules: image acquisition, preprocessing, and matching. In the image acquisition module, a finger body is illuminated appropriately by an NIR light source from above and the camera below the finger is used to capture the finger vein image. As the hemoglobin absorbs more NIR light than the surrounding tissue, e.g., fat, muscle, finger vein will be displayed as darker area and surrounding tissue will be displayed as lighter area in the captured image.

The completeness of the finger vein pattern has a big impact on the recognition rate. However, overexposure and underexposure will cause information loss, which usually could not be recovered through image enhancement. Therefore, it is necessary to adjust the illuminance distribution of lighting to eliminate overexposure and underexposure in the image acquisition process. In this way, the information of a finger vein pattern could be retained as much as possible in the acquired finger vein image.

In a lot of work, illuminance adjustment is realized manually, which is time consuming, and the consistency of the image quality could not be guaranteed. To solve these problems, proposed a self-adaptive illuminance control algorithm, which could quickly and automatically adjust illuminance distribution without human interference.

Nowadays there is an increased interest in modern societies with the development and deployment of internet and web technologies for methods that can verify or identify the identity of a user that access from a remote location. Traditional security systems as key locks or identification cards are also target for a modernization that can upgrade the security of critical locations such as ATMs, banks, nuclear power plants, etc.

Those and other different scenarios are pushing the development of more sophisticated systems based on biometrical information given the impossibility of a malicious individual to reproduce the information. Those systems are usually known as biometrical identification systems. Systems through pattern recognition can identify an individual by a unique biometrical feature. Theoretically, the ideal biometrical feature for human identification should include: easy to be extracted from an individual, hard to be access by general public and hard to be reproduced by anyone else.

II. LITERATURE SURVEY

Presently, finger-vein recognition is a new research direction in the field of biometric recognition. The Gabor filter has been extensively used for finger-vein recognition; however, its parameters are difficult to adjust. To solve this problem, an adaptive-learning Gabor filter is presented herein. We combine convolutional neural networks with a Gabor filter to calculate the gradient of the Gabor-filter parameters, based on the objective function, and to then optimize its parameters via back-propagation. The parameter θ of Gabor filter can be trained to the same angle as the vein texture of finger vein image. The parameter σ of Gabor filter has a certain relation with λ, and the parameter λ of Gabor filter can converge to the optimal value well. Using this method, we not only select appropriate and effective Gabor filter parameters to design the filter banks, we also consider the relationship between those parameters. Finally, we perform experiments on four public finger-vein datasets.

Biometrics-based authentication of subjects is widely deployed in several real-life applications. Among various biometric characteristics, finger-vein characteristic has demonstrated both reliable and highly accurate authentication for access control in secured applications. However, most of these systems are based on commercial sensors where the image level data is not available for academic research. In this paper, we present the design and development of a low-cost finger-vein sensor based on a single camera that can capture finger-vein images from dorsal and ventral part of the finger with high quality. The system consists of multiple Near-Infra-Red (NIR) light sources to illuminate the finger from both sides (left and right) and top. The camera in the sensor is also coupled with the custom designed physical structure to facilitate high reflectance of the emitted light and distribute the light uniformly on the finger to capture good quality dorsal and ventral finger-vein pattern. Extensive experiments are carried out on the data captured using the developed sensor and benchmarked the performance with eight different State-Of-The-Art (SOTA) algorithms. The results on a large-scale finger-vein dataset demonstrate the need for illumination from both sides (left and right) and from the top of the finger, to capture finger-vein images with high quality that improves the verification performance.

Deep convolutional neural networks (DCNN) have been applied successfully for finger vein recognition and have achieved promising performance in the past three years. However, public finger vein datasets are scarce and tend to be relatively small, and thus unable to provide a substantial number of welllabeled images needed to train an effective convolutional neural network (CNN). In this paper, a CNN model pre-trained on ImageNet is adopted to develop a CNN-based local descriptor named CNN competitive order (CNN-CO) that can exploit discriminative features for finger vein recognition. The CNN filters from the first layer of the AlexNet network and the corresponding CNN filtered images are visualized and compared with Gabor filters. According to the appearances and outputs of the CNN filters in three color spaces, we select the ones that most resemble the Gabor filters. The selected CNN filters are employed to generate a competitive order (CO) image using the winner-take-all rule. Then, the pyramidal histograms calculated from the CO image in different levels are concatenated to build the final histogram. The extensive experimental results on two public finger vein datasets demonstrate the effectiveness of the proposed method in selecting CNN filters. The results show that the proposed CNN-CO scheme using the selected CNN filters outperforms the well-known local descriptors.

Vein pattern-based methods powerfully boost the recognition accuracy of finger veins, but real-time recognition cannot be guaranteed, especially in large-scale applications. Moreover, previous studies focused on either the matching task to enhance the accuracy or the indexing task to improve the efficiency. This paper proposes a finger vein code indexing method and combines it with a finger vein pattern matching method into an integration framework for improving both accuracy and efficiency. With the extracted vein patterns, the direction of each vein segment is detected and represented by the elliptical direction map as a feature for indexing, which will be encoded into a binary code by the angle K-means. The similarity between vein direction codes is measured by the grouped hamming distance in indexing, and further weighted by the overlap degree of the corresponding vein patterns to return the candidates for the probe. In addition, based on the above distance measurement, only vein segments with the same direction code are considered in following probe-to-candidate matching.

Finger-vein recognition technology has attracted more and more attention because of its high security and convenience. However, the finger-vein image capturing is affected by various factors, which results that some vein patterns are missed in acquired image. Matching minutiae features in such images ultimately degrades verification performance of the finger-vein recognition system. To overcome this problem, in this paper, a novel finger-vein image restoration approach is proposed to recover the missed patterns based on generative adversarial network (GAN), as the first attempt in this area. Firstly, we employ the segmentation algorithm to extract finger-vein network, which is further subject to thinning operation. Secondly, the resulting thinning image is taken as an input of a GAN model to restore the missed vein patterns. Thirdly, the minutiae points are extracted from restoration finger-vein pattern. Finally, we propose a matching approach for verification. Experimental results show that the proposed method can restore the missed vein pattern and reduce the equal error rate (EER) of the finger-vein verification system

III. PROPOSED SYSTEM

The block diagram of the finger vein recognition system framework combining a primary biometric trait and the proposed soft biometric trait is depicted in Fig. 1

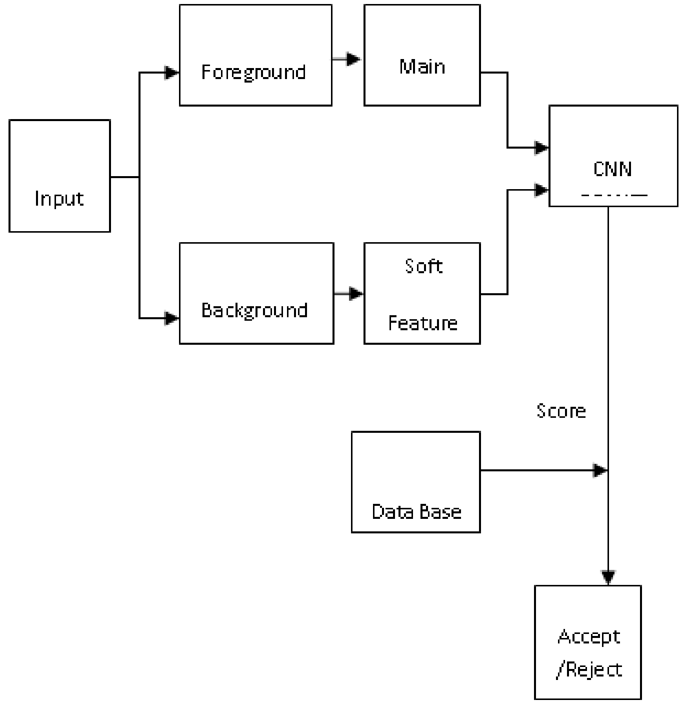


Fig 1 Proposed Block Diagram

First, separate the input image into a foreground layer image and background layer image using our proposed image layer separation. Next, the primary biometric trait is extracted from the foreground layer, and the soft biometric trait is generated from the background layer using different methods. Finally, the artificial neural network is used to authorize the person. The pixels in any region of a test image can then be classified effectively.

Propose a novel soft biometric trait for improving the performance of finger vein recognition, i.e., the intensity distribution in the background of the finger vein image. To the best of our knowledge, this is the first time that the intensity distribution has been investigated as one of the soft biometric traits of the finger vein.

Propose an effective method for extracting the intensity distribution as a soft biometric trait. Because the finger vein image is composed of the foreground layer, which contains the texture information, and the background layer, which contains the intensity distribution information, the proposed method first uses a background layer extraction algorithm to separate the intensity distribution from the finger vein image. Then, the intensity distribution is described in three ways. In classification stage developed a convolution neural network specifically resnet for the training image dataset and image retrieving process is done. Purpose of introducing deep learning in developing finger vein identification system is to get accurate more performance and speedy results.

Preprocessing

The first stage of preprocessing is image resizing, In images are the exact size need them to be. When an image is resized, its pixel information is changed. It returns an image that is SCALE times the size of input image. Histogram equalization enhances the contrast of images by transforming the values in an intensity image. It accomplishes this by effectively spreading out the most frequent intensity values, i.e. stretching out the intensity range of the image. This method usually increases the global contrast of images when its usable data is represented by close contrast values. This allows for areas of lower local contrast to gain a higher contrast.

Image Layer Separation

The foreground layer contains the texture information. Background layer contains the intensity distribution information. Gaussian blur (GB) seems to be a more intuitive method to obtain the background layer. Because the finger vein texture can be viewed as the high-frequency components and the intensity distribution in the background can be regarded as the low-frequency components. GB can be used as a low pass filter to filter out the finger vein texture, thereby leaving only the background layer.

Feature Extraction

Feature extraction a type of dimensionality reduction that efficiently represents interesting parts of an image as a compact feature vector. This approach is useful when image sizes are large and a reduced feature representation is required to quickly complete tasks such as image matching and retrieval. The different fingers have different structures, such as the position of the knuckle, the structure of the bone, the thickness of the finger, and the water content of the tissue, the intensity distributions of different finger veins are different after transmission imaging, which is often used for finger vein image acquisition.

Primary Biometric Trait Extraction

The primary biometric trait is the feature with the most powerful discrimination, which is key to ensuring the accuracy of the system. LBP is an efficient texture extraction algorithm with illumination and rotation invariance, which is usually applied to vein recognition. The main idea of LBP is to measure the gray change between each pixel and its neighborhood and to code this change to generate the LBP code histogram, which can fully represent the finger vein feature.

Soft biometric trait extraction

As a novel research field on biometrics, the usage of soft biometric traits has been investigated in recent years. Preliminarily discussed and proposed a framework for the integration of soft biometric traits. Since then, soft biometric traits have been investigated in depth. Recently, summarized the research details of soft biometrics and discussed the associated definition, benefits, applications, open research problems, and taxonomy. In, taxonomy of soft biometrics was presented, which considered four groups of attributes: demographic, anthropometric, medical, and material and behavioral attributes.

These four kinds of attributes, which are based on the modalities of the face, iris, body, gait, fingerprint, and hand, were comprehensively reviewed. The term demographics refer to attributes such as age, gender, ethnicity, and race, which are widely used in common population statistics. Anthropometric attributes usually refer to geometric and shape features of the face, body, and skeleton. Medical attributes are features that are related to body weight, body mass index, and skin color and quality.

Material and behavioral attributes are features that are related to eye lenses, glasses, According to the analysis, the main difference among individuals' background layers is the intensity distribution. For this characteristic, we design three kinds of soft biometric traits that are extracted from the background layer, i.e., the mean and variance, the array of mean and variance, and the histogram of spatial pyramid.

Mean and Variance

The thickness of the finger and the density of the tissue vary among individuals. These physical characteristics are reflected in the brightness and the contrast of the finger vein image

Array of Mean and Variance

The width of the knuckle and the length of the finger vary among individuals. Therefore, the bright region and the dark region have different spatial properties among individuals.

Histogram of Spatial Pyramid

Soft biometric traits Mean &Variance and Array of Mean &Variance extract the features in only one scale. To construct the features in multiscale, a spatial pyramid is used for sub-image partitioning, and the histogram is calculated in each sub-image. As shown in Fig. 5, the finger vein image is partitioned by two scale grids. Then, we calculate the grayscale histogram of each image block. The concatenation of these histograms in each block is called as Histogram of Spatial Pyramid (HSP).

CLASSIFICATION

A CNN or convolution neural network is a grouping of layers, and each layer changes one volume to another through differentiable functions. There are various types of layers in CNN. I should take a model by running a covnets on of picture of measurement 320*240.

Information Layer

This layer holds the raw contribution of picture with width 320, height 240.

Convolution Layer

This layer computes the output volume by figuring dot product between all channels and picture fix.

Actuation Function Layer

This layer will apply component apply initiation function to the yield of convolution layer. Some basic actuation functions are RELU: max(0, x), Sigmoid: 1/(1+e^-x), Tanh, Leaky RELU, and so on.

Pool Layer

This layer is intermittently embedded in the covnets and its fundamental function is to decrease the size of volume which makes the calculation quick lessens memory and furthermore keeps from overfitting. Two normal sorts of pooling layers are max pooling and normal pooling. CNN could be a gradable neural network that usually extracts features options by convolving input with a gaggle of kernel filters. Then pooling of obtained feature is done and filtered resolute next layer. within the following, we are going to introduce CNN algorithm.

Despite the fact that the system is pre-prepared on scene and article pictures, it has illustrated, in primer analyses, to work far superior to a ResNet-18 pre-prepared on texture of pictures. The visual appearance of texture is surely increasingly like the visual appearance of the finger vein detection images considered right now. Despite this, the exhibition gotten by misusing the texture domain organize are a lot of more awful than the presentation got utilizing a scene- and article space one. All things considered, perceiving scenes and items is progressively entangled than perceiving surfaces, and in this way the system prepared to perceive scenes and items is progressively skilled of perceiving surprising irregular examples inside finger vein detection picture.

ALGORITHM

Soft biometric trait extraction Algorithm
Mean and Variance
Let (x,y) be the background layer image, and w and h be the width and the height of the image, respectively.

$$M = \frac{\sum_{i=1}^{wh} I_i(x,y)}{wh}$$

The variance V is:

$$V = \frac{\sum_{i=1}^{wh}(I_i(x,y) - M)^2}{wh}$$

$$f_1 = [M, V]$$

Array of Mean and Variance
The width of the knuckle and the length of the finger vary among individuals. Therefore, the bright region and the dark region have different spatial properties among individuals. To describe these characteristics, the background layer image is divided into $a \times b$ blocks. The grayscale mean m and grayscale variance v $(1 \leq i \leq a \times b)$ of each block are concatenated to obtain the $2 \times a \times b$ -dimensional soft i biometric trait, which is the array of mean and variance (AM&V):

$$f_2 = [m_1, v_1 \ldots m_i, v_i](1 \leq ia \times b)$$

Local Binary Pattern

Parameters: the LBP uses 4 parameters:

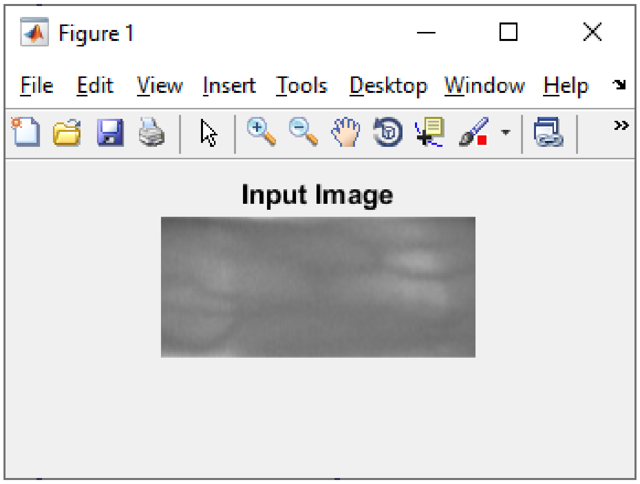
Radius: the radius is used to build the circular local binary pattern and represents the radius around the central pixel. It is usually set to 1.

Neighbors: the number of sample points to build the circular local binary pattern. Keep in mind: the more sample points you include, the higher the computational cost. It is usually set to 8.

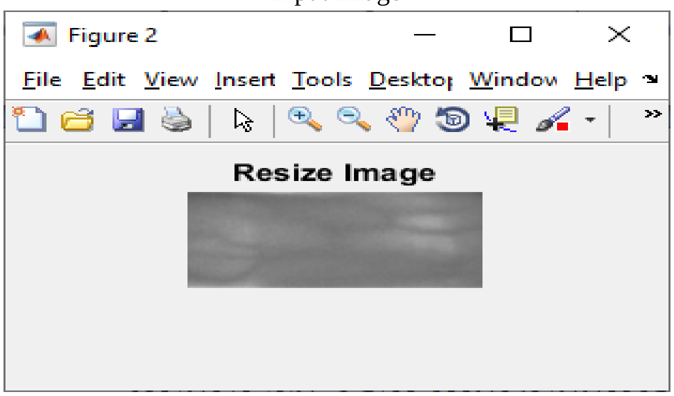
Grid X: the number of cells in the horizontal direction. The more cells, the finer the grid, the higher the dimensionality of the resulting feature vector. It is usually set to 8

Grid Y: the number of cells in the vertical direction. The more cells, the finer the grid, the higher the dimensionality of the resulting feature vector. It is usually set to 8.

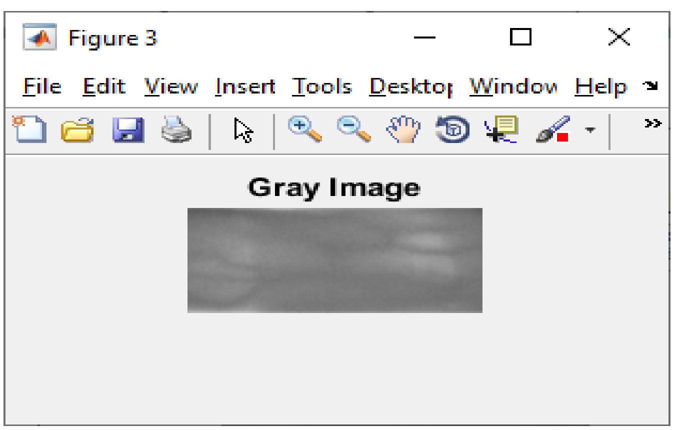
IV. SCREEN SHOTS



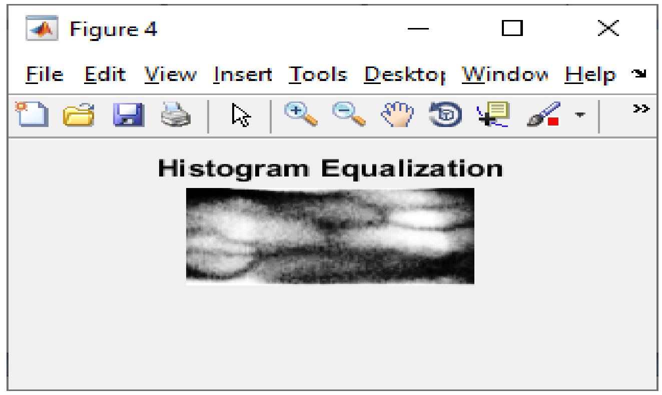
Input Image



Resize Image



EEG Gray Image



Histogram Equalization

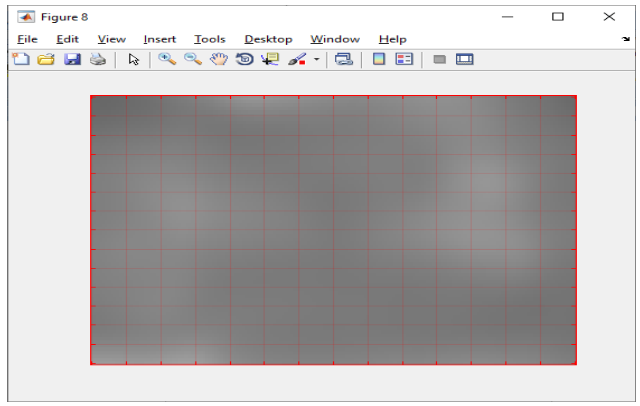
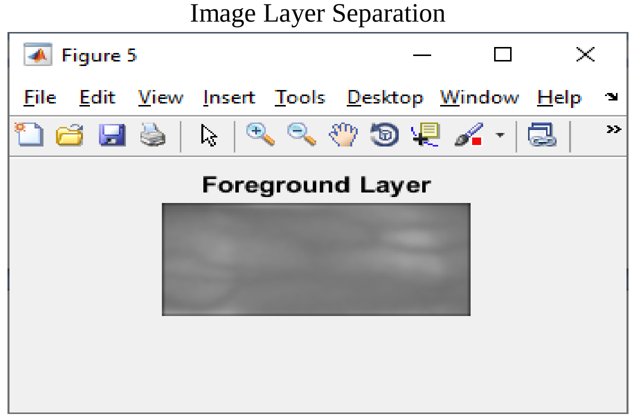
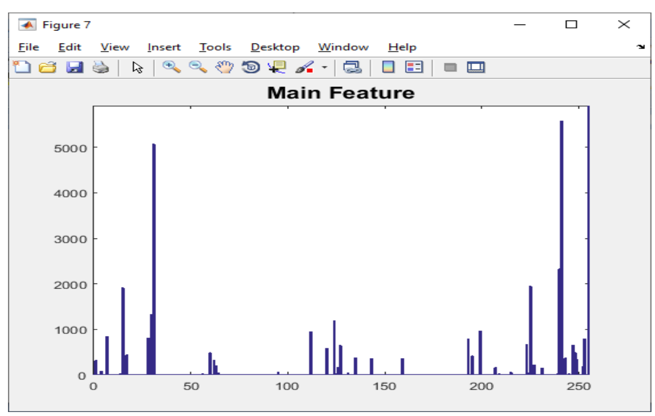


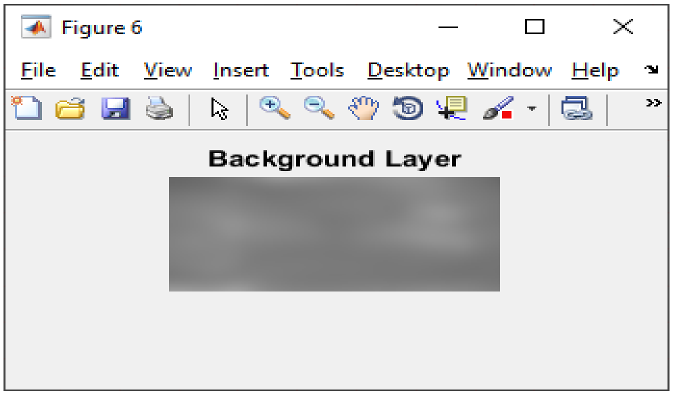
Image Layer Separation



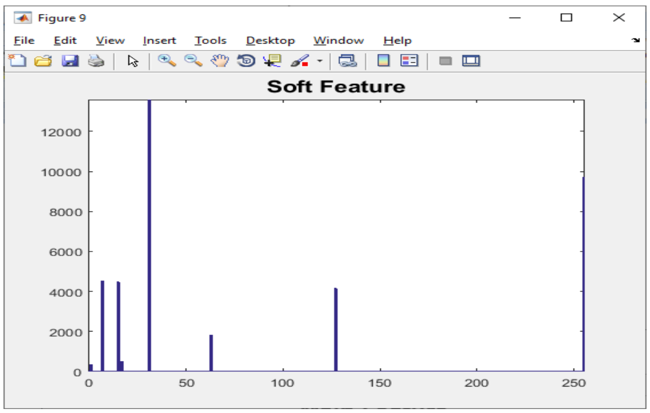
Foreground Layer



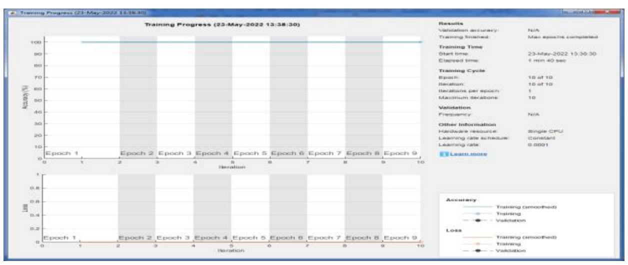
Main Feature

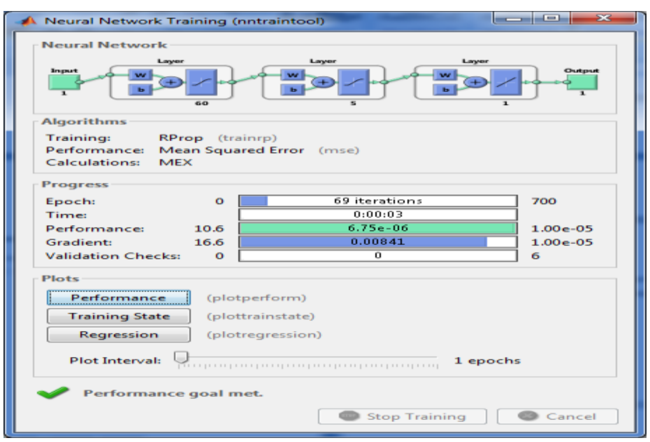


Background Layer

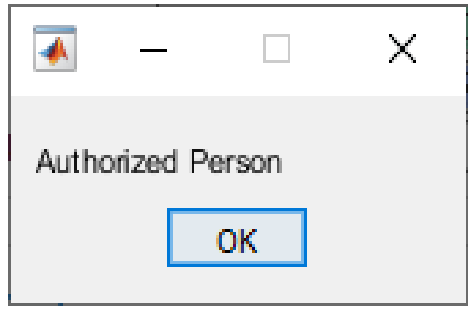


Soft Feature





CNNResNet Classifier



Authentication dialogue box

V. CONCLUSION

In the past, most research of finger vein recognition only focuses on the texture feature of finger veins but gives little attention to the intensity distribution in the background, even regarding the intensity distribution as the noise. This paper analyzes the theory of finger vein imaging and the features in the image and proposes a soft biometric trait extraction algorithm. First, the background layer without finger vein texture is extracted with ILS and GB. Then, the intensity distribution in the background layer is described by three soft biometric traits. Finally, a CNNRESNET 18 for improving the matching accuracy of the primary biometric trait and the soft biometric trait is proposed. CNN has highest accuracy among other techniques; it has accuracy of 99.98%. The experimental results showed that GB is less time-consuming than ILS but achieves equivalent performance.

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