An Efficient Approach For Finger Vein Recognition Using Artificial Neural Network

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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. Finally, a training dataset is constructed based on the patches centered on the labeled pixels. Secondly, an artificial neural network (ANN) is trained on the resulting dataset to predict the probability of each pixel of being foreground given a patch centered on it. The ANN learns what a finger vein pattern is by learning the difference between vein patterns and background ones. The pixels in any region of a test image can then be classified effectively. The identification performance of the system is evaluated using the recognition rate.*

Keywords- Biometrics; finger-vein; Artifical Neural Network; Biometric trait extraction.

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.

The acquisition of biometric parameters is a very hard procedure since it requires the conditions around the acquired parameter be as similar as possible. To achieve this target, it's necessary to make a combination between hardware design and software procedures. Through hardware design, the system may instruct the user to perform properly to make the pattern recognized easily. Through software procedures, the system may correct the problems related to the acquisition of the pattern, relying on algorithms that aid to solve irregularities. Furthermore, the algorithm is able to create the score of similarity in biometrical character from extracted fingerprints, the result of which is assumed to be accurate with infinite decimal. Fingerprint identification is one of the most common biometric systems to identify individuals.

A. Existing System

Miura proposed a technique that's supported hard curvatures in cross-sectional profiles of a vein image. In each profile, the location of the most curvatures is found, and those maxima and also theirs dimensions area unit taken because the center and the width of the veins severally. A new method has been developed to robustly extract the precise details of the veins by hard native most curvatures within the cross-sectional profiles of a vein image. The positions are interconnected with every alternative and at last the vein pattern is detected. The drawback of existing system is Time consuming, Image quality could not be guaranteed, It provide high personal identification error rate, High false rate.

B. *System Model*

Finger vein recognition system framework combining a primary biometric trait and the proposed soft biometric trait is depicted. First, separate the input image into a foreground layer image and background layer image using proposed image layer separation strategy. 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. Then, proposed a hybrid matching strategy to match the primary and the soft biometric trait, that is, matching the primary biometric trait with SVM yields the main score. Finally, the SVM main score is compare to the data base score and produce high accuracy result.

The rest of the paper is organized as follows. In Section II the system model is proposed system. In Section III numerical simulations are presented. Finally in Section IV a conclusion is drawn.

II. PROPOSED SYSTEM

Propose a new and effective soft trait of the finger vein based on the analysis of finger vein imaging theory. The flow chart of the finger vein recognition system framework combining a primary biometric trait and the proposed soft biometric trait is depicted in Fig. 1.1. First, separate the input image into a foreground layer image and background layer image using our proposed image layer separation strategy.

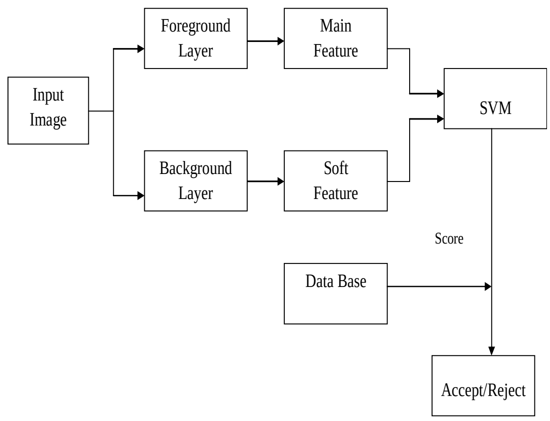

Fig 1.1 Block Diagram

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.

Then, proposed a hybrid matching strategy to match the primary and the soft biometric trait; that is, matching the primary biometric trait with SVM yields the main score, and matching the soft biometric trait with the Manhattan Distance yields the soft score. Finally, we normalize the two scores and fuse them based on the weighted sum rule to generate the final matching score.

In this project first analyze the imaging principle and explain why the intensity distribution in the background can be used as a novel soft biometric trait. Second, two background layer extraction algorithms and three soft biometric trait extraction algorithms are proposed for describing the intensity distribution. Finally, because there are significant differences in dimension between soft and primary biometric traits, existing matching strategies cannot achieve desirable performance; thus, we propose a hybrid matching strategy for fusing the primary and soft biometric traits for more robust finger vein recognition. This algorithm matches the primary biometric trait with SVM and the soft biometric trait with the Manhattan Distance.

The results of a series of rigorous contrast experiments on three public databases indicate that our exploration of soft biometric trait extraction and matching is feasible and effective for a finger vein recognition system. The main contributions of this work are as follows: 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. We 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. The hybrid matching strategy is adopted to match the primary and soft biometric traits, which can further improve the matching performance. We conduct thorough experiments on three databases. Our method significantly outperforms previous state-of-the-art methods in terms of overall recognition performance.

A. Background Layer Extraction

In addition to the texture feature, which is commonly included in finger vein images, the intensity distribution, which is formed by the unique tissue constitution and distribution inside every finger, can also be treated as a feature. To extract the pure intensity distribution, the finger vein texture should be filtered out from the vein image, thereby leaving the neat background layer that is generated by other tissue. Since there have been no specific studies on it, propose two algorithms for achieving this objective, i.e., image layer separation and Gaussian blur.

Image Layer Separation

Image layer separation (ILS) is a type of algorithm that separates an image into a smooth layer and a high-gradient layer, which is commonly used for intrinsic image decomposition and single-image reflection interference removal. Among all types of ILS algorithms, a relative smoothness-based method is adopted as a comparison algorithm in this paper to solve the ILS issue for separating the finger vein image. This algorithm used the half-quadratic separation scheme and a normalization algorithm to separate a finger vein image into a foreground layer and a background layer. The foreground layer contains the texture information, and the background layer contains the intensity distribution information. Thus, the adopted ILS algorithm is a valid method to separate the finger vein image.

Gaussian Blur

Besides the ILS algorithm, 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, However, GB is more efficient than ILS and has better noise suppression performance.

B. 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. Many algorithms for finger vein primary biometric trait extraction have been introduced in Section II. Among them, LBP, Weber Local Descriptor (WLD), Histogram of Oriented Gradients (HOG), and Scale Invariant Feature Transform (SIFT) are the typical methods for achieving the described performance. In this paper, they are also used as the primary biometric trait extraction algorithms to evaluate the performance of our soft biometric traits. LBP is an efficient texture extraction algorithm with illumination and rotation invariance, which is usually applied to face recognition and 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 but cannot handle the texture transition. WLD is also a popular texture extraction algorithm. Compared with LBP, WLD includes not only the gray information but also the gradient information.

WLD calculates he gray-value difference between each pixel and its neighborhood, and measures the gradient information in the horizontal and vertical directions. As an efficient texture extraction algorithm, HOG was initially used for pedestrian detection. The major strategy of HOG is to divide the image into several cells, which are used to calculate the histogram of gradients. Then, the cells are divided into several blocks with overlapping regions to alleviate the impact of target rotation, which makes it possible for HOG to handle rotation around the finger in the finger vein recognition system. SIFT has been proven to be one of the most robust local feature descriptors in object recognition and matching. Difference of Gaussians was proposed for corner detection to improve the calculation efficiency, and the cardinal direction of the descriptor also makes it robust to object rotation.

C. 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.

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 refers 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, 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. Let (x, y) be the background layer image, and w and be the width and the height of the image, respectively.

Then, the grayscale mean M is:

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

The variance V is:

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

And the soft biometric trait of the mean and variance (M&V) is:

$$f_1 = [M, V] \quad (3)$$

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):

$$f_2 = [m_1 v_1 \ldots m_i v_i](1 \leq ia \times b) \quad (4)$$

Histogram of Spatial Pyramid

Soft biometric traits M&V and AM&V 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. The finger vein image is partitioned by two scale grids. Then, calculate the grayscale histogram of each image block. The concatenation of these histograms in each block is called as Histogram of Spatial Pyramid (HSP).

III. RESULT AND DISCUSSION

Fusion of the soft and primary biometric traits can yield better performance than using the primary biometric trait alone, which demonstrates that the background layer of the finger vein image also contains useful identity information, which can lead to better discrimination among subjects. In this section use the PSNR and MSE to test the feature value of soft and primary biometric traits. The comparison among the improved algorithm and other two feature extraction algorithm are also presented.

In this section, give the experimental results of the proposed feature extraction algorithm. 10 MMCBNU test images are selected to test the feature extraction stage, which are either in 117x74 sizes. Finally, the feature of the common region of finger vein images is extracted as the primary feature from primary biometric traits, two background layer extraction algorithms, and the three soft biometric traits that are mentioned. In addition, all experiments in this project are conducted with MATLAB R2016a.

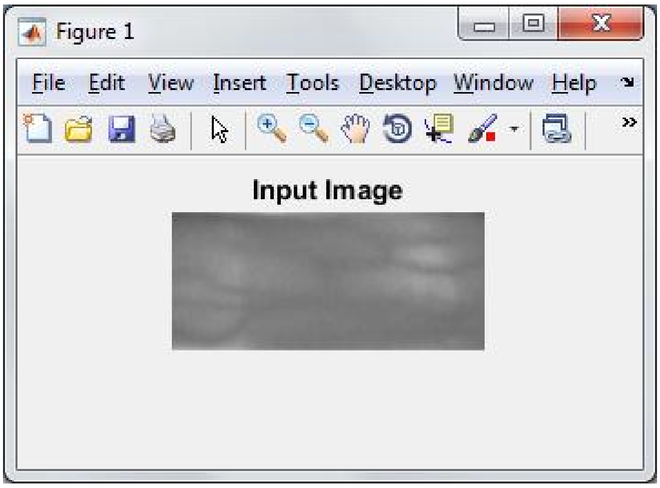

Fig 1.2 Input Image

Fig 1.3 Resizes Image

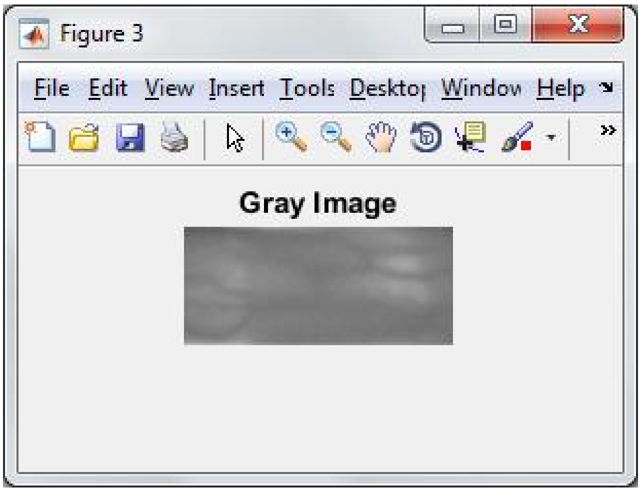

Fig 1.4 Gray Image

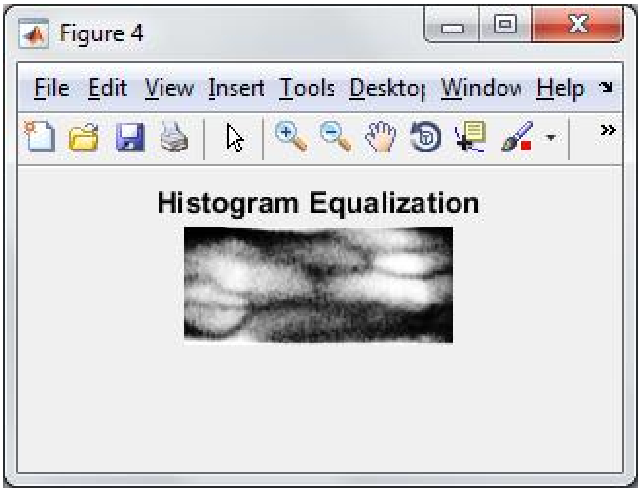

Fig 1.5 Histogram Equalization

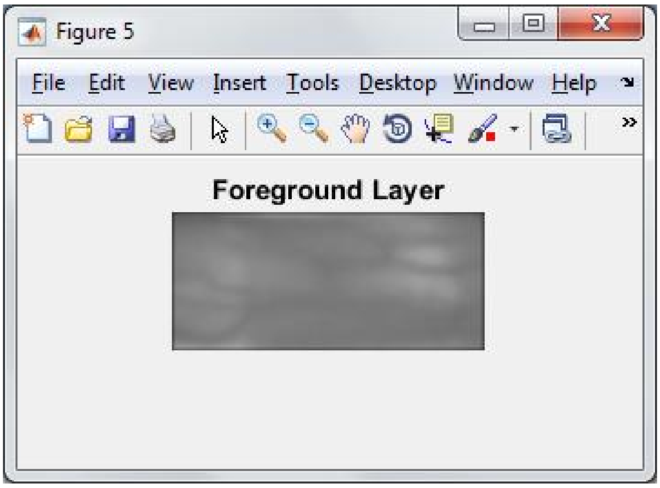

Fig 1.6 Foreground Layer

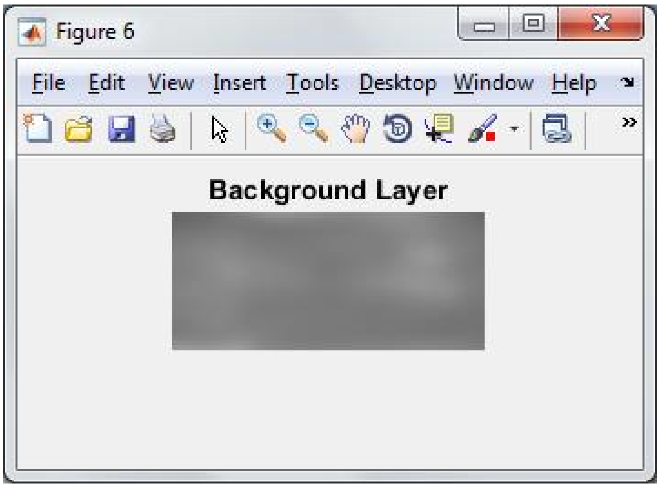

Fig 1.7 Background Layer

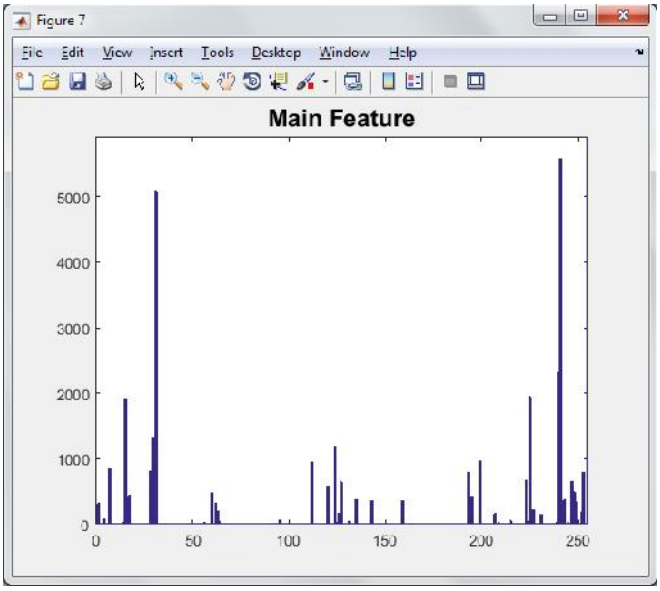

Fig 1.8 Main Feature

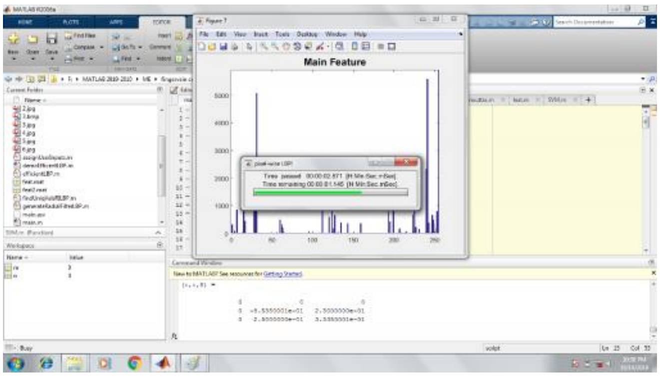

Fig 1.9 Wait Bar Time Remaining

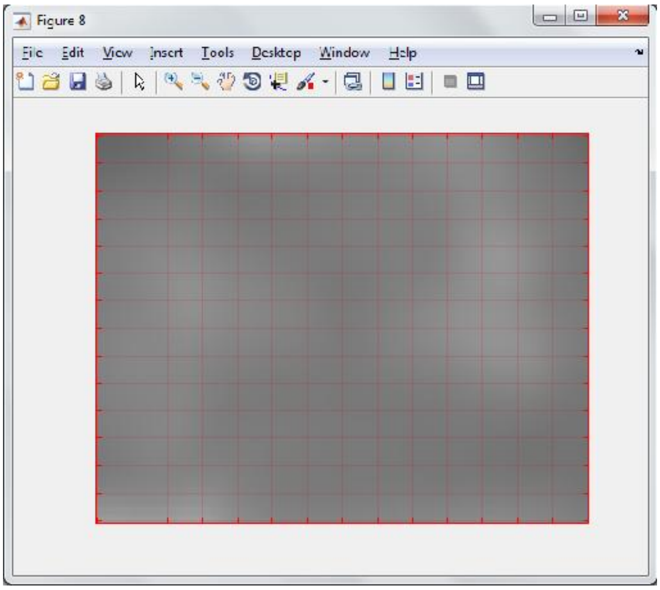

Fig 1.10 Image Layer Separation

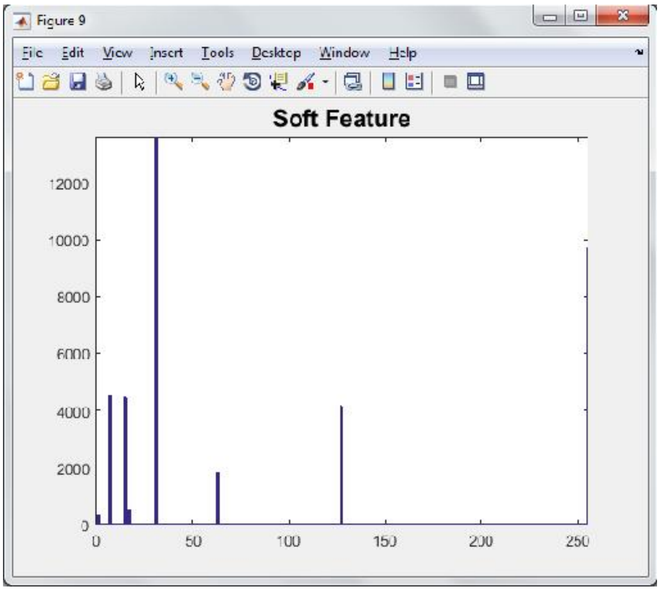

Fig 1.11 Soft Feature

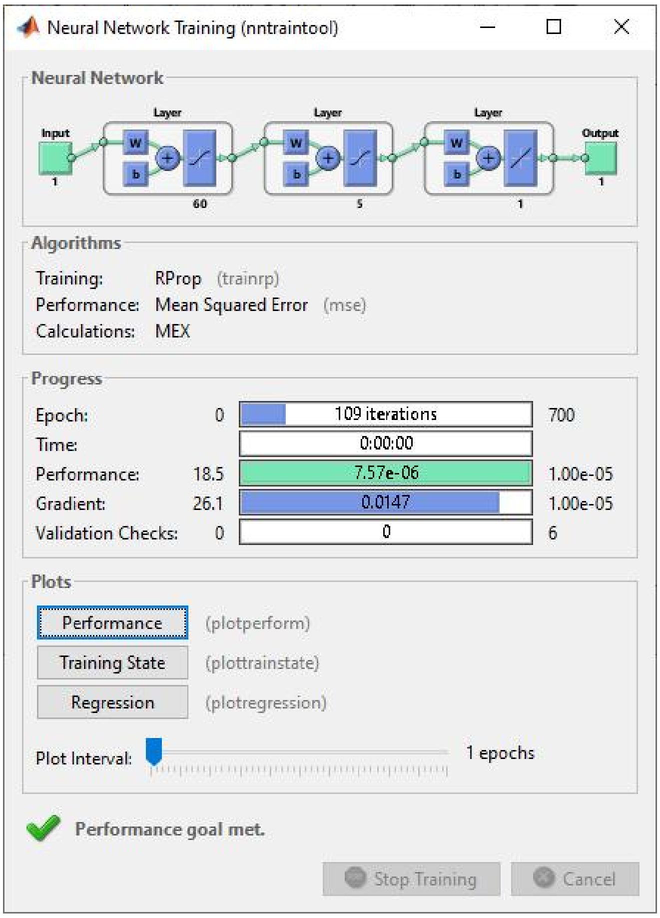

Fig 1.12 Artificial neural network

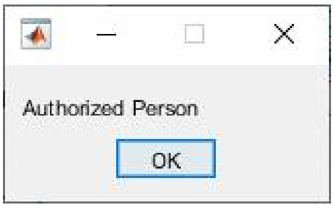

Fig 1.13 Authentication dialogue box

IV. 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 project 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. The performance of the soft biometric trait remains stable over a series of sigma changes, which demonstrates that the soft biometric trait in the background layer is robust.

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