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Palm Vein Recognition for Human Identification Using NN

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Abstract— In the ubiquitous network society, where individuals can easily access their information anytime and anywhere, people are also faced with the risk that others can easily access the same information anytime and anywhere. Because of this risk, personal identification technology, which can distinguish between registered legitimate users and imposters, is now generating interest. Currently, passwords, Personal Identification cards are used for personal identification. However, cards can be stolen, and passwords and numbers can be guessed or forgotten. To solve these problems, biometric authentication technology, which identifies people by their unique biological information, is attracting attention. Palm vein recognition is that it is not affected by dryness or roughness of skin or by physical injury on surface of the hand but sometimes the temperature and humidity can affect the quality of the captured image.

Index Terms— Feature Extraction, Palm Vein Recognition System, NN.

I. INTRODUCTION

Biometrics is the unique feature of a person. Biometric recognition refers to an automatic recognition of individual based on feature vectors derived from their physiological and/or behavioral characteristic. Biometric systems for human identification at a distance have ever been an increasing demand in various significant applications [1].

Vein recognition was first developed by Joseph Rice [2]. In 1984 he had his identity stolen, which led to fraudulent use of his bank account. He decided to do something about it, which led to his first vein recognition prototype around1985. Biometric techniques can generally be classified into two main categories: Physiological and Behavioral. Physiological techniques include fingerprint recognition, retinal and iris scanning, facial recognition, hand and finger geometry and DNA analysis. Behavioral techniques include handwriting recognition, voice authentication, vein, and key stroke dynamics just to name a few [3]. Main advantage of palm vein recognition is that it is not affected by dryness or roughness of skin or by physical injury on surface of the hand but sometimes the temperature and humidity can affect the quality of the captured image. Even though is little bit expensive it is highly adaptable as it is highly secure because blood vessels are hidden within the body. And also in this there is no physical contact between the user and system but it causes apprehension. Palm vein pattern recognition is a convenient and easy to use biometric technology with high security and accuracy level.

There are mainly far infrared scanning technology and near infrared scanning technology and there are thermal hand vein pattern verification systems for security evaluation of biometric systems. Today, this technology plays a major role in providing authentication.

Palm vein biometric system can verify a person's identity by recognizing the pattern of blood veins in the palm. Palm vein authentication [4] uses the vascular patterns of an individual's palm as personal identification data.

Figure 1. Extracted vein image

Like fingerprints, the pattern of blood veins in the palm is unique to every individual, even twins have different patterns and apart from size, this pattern will not vary over the course of a person's lifetime. The palm is an ideal part of the body for this technology; it normally does not have hair which can be an obstacle for photographing the blood vessel pattern, and it is less susceptible to a change in skin color, unlike a finger or the back of a hand [3].

II. FINGER-PALM IMAGE PREPROCESSING

The acquired images are noisy with rotational and translational variations resulting from unconstrained imaging [5]. Therefore, the acquired images were first subjected to pre-processing steps that include:

1) Segmentation of ROI,
2) Translation and orientation alignment, and
3) Image enhancement to extract stable/reliable vascular patterns.

The enhanced and normalized ROI images are employed for feature extraction.

The key objective while segmenting the ROI was to automatically normalize the region in such a way that the image variations, caused by the interaction of the user with the imaging device, can be minimized.

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In order to make the identification process more effective and efficient, it was necessary to construct a coordinate system that was invariant/robust (or nearly) to such variations. It was judicious to associate the coordinate system with the palm itself since we were seeking the invariance corresponding to it. Therefore, two webs were utilized as the reference points/line to build up the coordinate system i.e., the web between the index finger and middle finger together with the web between the ring finger and little finger [Fig. 2]. These web points were easily identified in touch-based imaging (using pegs) but should be automatically generated for contactless imaging [10].

The acquired palm images were first binarized [see Fig. 2], so that we were able to separate the palm region from the background region. This was followed by the estimation of the distance from centre position of the binarized palm to the boundary of palm.

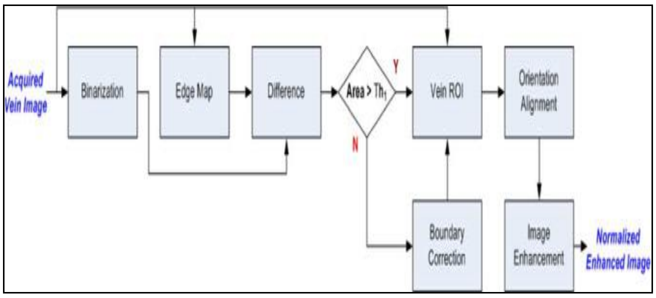

Figure 2. Block diagram illustrating key steps employed for the pre-processing of acquired finger-PALM images.

The block diagram of the proposed system is shown in Fig.1. The fingers presented for the identification of subjects were simultaneously exposed to a webcam and an infrared camera, as illustrated from the device of our imaging device in Fig. 2. The[11] dorsal side of a finger is exposed to the near-infrared frontal surface illuminators, using light-emitting diodes whose illumination peaks are at a wavelength of 850 nm, whereas the frontal surface entirely remains in the contactless position with both of the imaging cameras. Although our imaging system is unconstrained, i.e., it does not use any pegs or finger docking frame, it may not be designated as completely touchless. This is because the user often partially or fully touches the finger dorsal surface with the white diffusion background, which holds the infrared illuminators beneath. The finger-vein and finger texture images were simultaneously acquired using the switching device/ hardware that can switch the infrared illumination at a fast pace[12].

III. RECOGNITION

Once we obtain palm vein features, the next step is vein recognition. In this section, we introduce Neural Network. We give a brief description of the Neural Network method.

Neural Networks

Artificial neural networks are composed of interconnecting artificial neurons (programming constructs that mimic the properties of biological neurons) [6]. Artificial neural networks may either be used to gain an understanding of biological neural networks, or for solving artificial intelligence problems without necessarily creating a model of a real biological system. The real, biological nervous system is highly complex: artificial neural network algorithms attempt to abstract this complexity and focus on what may hypothetically matter most from an information processing point of view.

Neural networks give effective results for solving multiple class classification problems. The neural network facilitate gate recognition because of their highly flexible and non linear modelling ability. Neural network has three types of layers: input layer, output layers and hidden layers. Hidden layer does intermediate computation before directing the input to output layer. Back propagation can also be considered as a generalization of delta rule. When back propagation network is cycled, an input pattern was propagated forward to the output units through the intervening input to hidden and hidden to output weights [7]. Neural network have been widely used in image and signal processing.

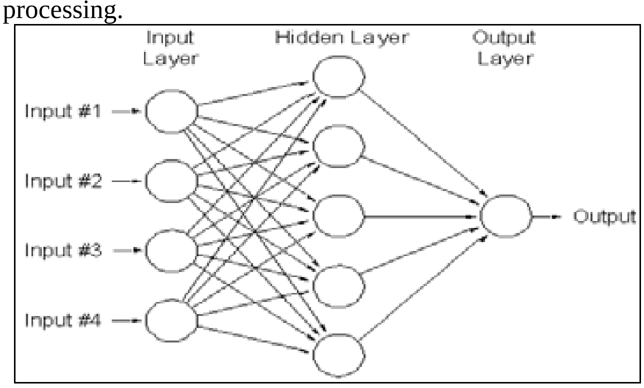

Figure 3: Basic layout of the Neural Networks

This class of networks consists of multiple layers of computational units, usually interconnected in a feed-forward way. Each neuron in one layer has directed connections to the neurons of the subsequent layer[8]. In many applications the units of these networks apply a sigmoid function as an activation function. The universal approximation theorem for neural networks states that every continuous function that maps intervals of real numbers to some output interval of real numbers can be approximated arbitrarily closely by a multi-layer perceptron with just one hidden layer. This result holds only for restricted classes of activation functions, e.g. for the sigmoidal functions. Multi-layer networks use a variety of learning techniques[9], the most popular being back-propagation. Here, the output values are compared with the correct answer to compute the value of some predefined error-function. By various techniques, the error is then fed back through the network. Using this information, the algorithm adjusts the weights of each connection in order to reduce the value of the error function by some small amount. After repeating this process for a sufficiently large number of training cycles, the network will usually converge to some state where the error of the calculations is small. In this case, one would say that the network has learned a certain target function. To adjust weights properly, one applies a general method for non-linear optimization that is called gradient descent. For this, the derivative of the error function with respect to the network weights is calculated, and the weights are then changed such that the error decreases (thus going downhill on the surface of the error function) [10].

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For this reason, back-propagation can only be applied on networks with differentiable activation functions.
The following are the various outcomes of the proposed system.

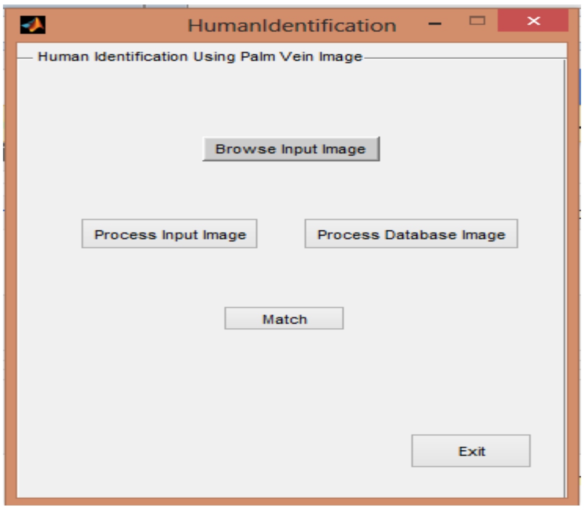

Figure 4. Basic GUI of the proposed system

By clicking on the 'Browse input image' button we get the following outcome.

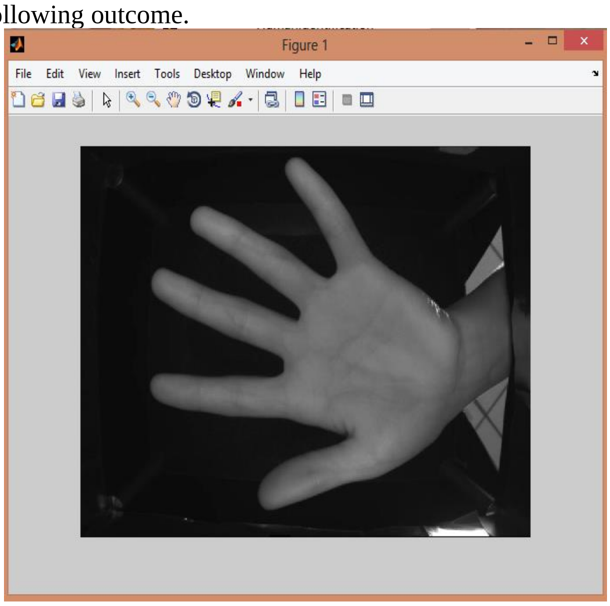

Figure 5. Palm Image

The above figure is produced from which we will select the specific region that we need to recognize.
The following are the outcomes of the second and third button i.e. process input image and Process Database image.

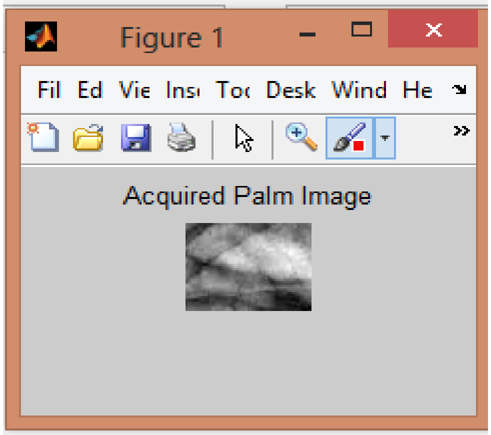

Figure 6. Acquired palm Image

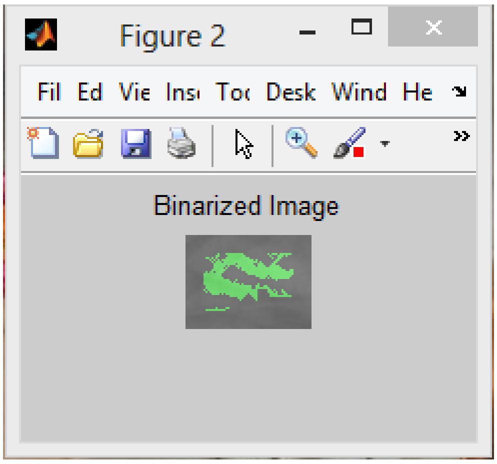

Figure 7. Binarized Image

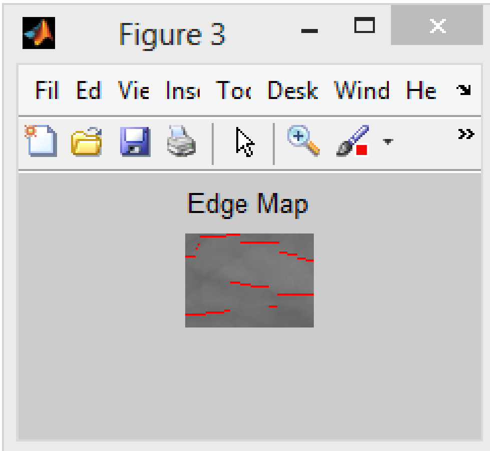

Figure 8. Edge Map

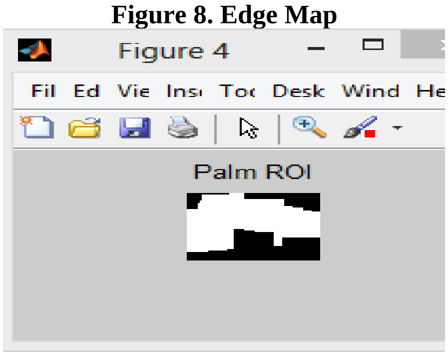

Figure 9. Palm ROI(Region of Interest)

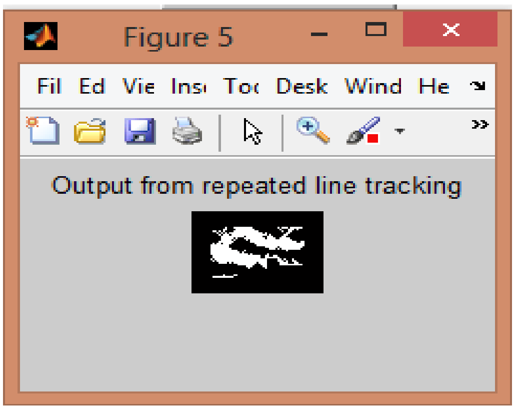

Figure10. Output from repeated line tracking

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The matching will be done through the match button and the proposed work will be done on the basis of the Neural Network in future.

IV. CONCLUSION

This paper will present a complete and fully automated palm image matching framework by simultaneously utilizing the palm surface and palm subsurface features, i.e., from palm-vein images.
This will present a new algorithm for the palm-vein identification, which can more reliably extract the palm-vein shape features and achieve much higher accuracy than previously proposed palm-vein identification approaches. Our palm -vein matching scheme will work more effectively in more realistic scenarios and leads to a more accurate performance and promotes high user's acceptance level, as will be demonstrated from the experimental results. We will examine a complete and fully automated approach for the identification of low resolution palm-surface for the performance improvement.
The proposed algorithm is an alternative to currently employed palm-vein identification approaches that do not take advantage from the cross-level image measurements. Further improvement in the performance from the proposed approaches using feature discretization and image quality measurements is expected and suggested for the further work on the large-scale palm image databases with the help of Neural Networks.

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