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RECOVERING FINGER-VEIN AUTHENTICATION BASED ON FEATURE EXTRACTION USING SVM

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ABSTRACT

Finger-vein biometrics has been extensively investigated for personal verification. Despite recent advances in finger vein verification, current solutions completely depend on domain knowledge and still lack the robustness to extract finger-vein features from raw images. A deep learning model to extract and recover vein features using limited a priori knowledge. Firstly, based on a combination of known state of the art handcrafted finger-vein image segmentation techniques ,so automatically identify two regions: a clear region with high separability between finger-vein patterns and background, and unambiguous region with low separability between them. The first is associated with pixels on which all the segmentation techniques above assign the same segmentation label(either foreground or background), while the second corresponds to all the remaining pixels.This scheme is used to automatically discard the ambiguous region and to label the pixels of the clear region as foreground or background. A training dataset is constructed based on the patches centered on the labeled pixels. Secondly, a Convolution Neural Network (CNN) is trained on the resulting dataset to predict the probability of each pixel of being foreground (i.e. vein pixel) given a patch centered on it. The CNN 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. Thirdly, we propose another new and original contribution by developing and investigating a Fully Convolution Network (FCN) to recover missing

Keywords: Hand bio metrics, Convolution neurallnetwork(CNN), FullyConvolution Network(FCN),Support vector machine(SVM.).

I.INTRODUCTION

Finger vein verification is used for personal verification. That is completely depend on domain knowledge and lack of robustness to extract finger vein feature from raw images so proposed deep learning model to extract using a priori knowledge Using state-of-the-art shandcrafted finger –vein image segmentation techniques is used to identify two regions: clear region between finger vein pattern and background(based pixel)and ambiguous region with low separability between them .Its is automatically discarded ambiguous region and show clean region as background and foreground. Using this techniques training data set is constructed. Convolution neural network(CNN) is predict the probability of each pixel being foreground.using fcn(fullyconvolution network)recover missing image finger vein pattern. Using this technique Improve accuracy of finger vein verification.

The blood vessels, as part of circulatory system, transport blood throughout the body to sustain the metabolism, using a network of arteries, veins and capillaries. The usage of such vascular structures in the palm, palm-dorsal and fingers has been investigated in the biometrics literature [2]-[9], [33]-[35] with high success.

The finger vein patterns are believed to be quite unique, even in case of identical twins and even between the different fingers an individual. There are two key factors that are cited for the preference of finger vein biometrics; firstly, the finger veins are hidden structures, it is extremely difficult to steal the finger vein patterns of an individual without their knowledge and therefore offering high degree of privacy. Secondly, the usage of finger vein biometrics offers strong anti-spoofing capabilities as it can also ensure liveness in the presented fingers during the imaging. Personal identification using finger vein patterns has invited lot of research interest [1]-[9] and currently several commercial products are available for civilian applications [24], [29]-[30]. The biometrics identification from finger vein patterns using normalized cross correlation of finger vein images is detailed in [7]. Miura et al. [5] have further improved the performance for the vein identification using repeated line tracking algorithm. The robustness in the extraction of finger vein patterns can be significantly improved with the usage of local maximum curvature across the vein images and is detailed in reference [6] with promising results. Wu and Ye [3] have successfully investigated finger vein identification using Radon transform based statistical features and probabilistic neural network classifier. However the database employed in this work is too small to generate reliable conclusion on the stability of such features in the noisy vein patterns.

The curvelet based extraction of finger vein patterns and its classification using back propagation neural network is described in [4]. The performance from this approach is shown to be very high but the key details of their implementation are missing in the paper. Lee and Park [2] have recently investigated the restoration of finger vein images using point spread function. Authors suggest significant improvement in the performance for the vein identification using such restored finger images. The finger vein imaging setup illustrated in [2]-[4], [7]-[9] is rather constrained and restricts the rotation or the movement of fingers during the imaging. A survey of prior work on finger vein identification suggest that although researchers have illustrated highly promising results, this area lacks systematic study, comparative evaluation of performance from (would be promising) previously proposed approaches and importantly there is no publicly available finger vein database that researchers can utilize for performance comparison and benchmarking.Human hands are easier to present, convenient to be imaged, and can reveal variety of features that can be observed with variety of illuminations (visible, near infra red, thermal infrared) and in wide range of imaging resolutions. In addition to fingerprints features [19], the palmprint [27], finger

II.RELATED WORK

The finger-vein recognition system also has the same construction [13].During preprocessing, the features of a finger-vein are extracted considering the specified region-of-interest (ROI), image resizing, image enhancement, and image alignment. The previous studies on finger-vein recognition mainly focused on preprocessing and feature extraction methods. In addition, some studies have applied Gabor filters of various directions and shapes to find the vein pattern [14,15,16,17,18,19,20,21,22]. Yang et al. proposed a method of finger-vein recognition, which involved extracting the features into 16 types of filters considering two scales, eight channels, and eight center frequencies of Gabor filters [15]. Peng et al. proposed a recognition method that is robust to scale and rotation, for which they designed an 8-way filter that selects the optimal parameters of the Gabor filter to extract the finger-vein features and applies the scale invariant feature transform (SIFT) algorithm to the features [18]. Yang et al. suggested a method of improving the contrast of the finger-vein pattern in the image using multi-channel even-symmetric Gabor filters with four directions [19]. Furthermore, in [20], they improved the quality of the finger-vein image by combining Gabor filtering with Retinex filtering based on a fuzzy inference system. In [21], they improved the quality of the finger-vein image through an optimal Gabor filter design based on the direction and thickness estimation of the finger-vein lines. Zhang et al. proposed gray-level grouping (GLG) in order to enhance the image contrast and a circular Gabor filter (CGF) to improve the quality of the finger-vein images [22]. In [23], both Gabor filter-based local features and global features of the moment-invariants method are used. In [24], they used an eight-channel Gabor filter to extract the features that were analyzed prior to the application of score-level fusion to obtain the final matching score.

III.PROPOSED SYSTEM

In this proposed work doing segmentation foreground pixel from background pixels by predicting the probability of the pixel belong to a vein pattern given limited knowledge. Recovering missing pattern using fully convolution network

3. 1 Convolutional Neural Network

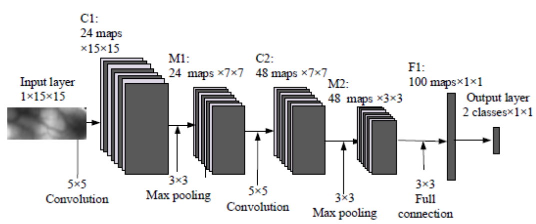

FIG 1 :Architecture of CNN

A CNN-based scheme is employed to automatically learn features from raw pixels for finger-vein verification. First, a dataset is constructed based on patches centered on the labeled pixels, and we take the patches as input for CNN training. Secondly, in the test phase, the patch of each pixel is input into CNN the output of which is taken as the probability of the pixel to belong to a vein pattern. Then, the vein patterns are segmented using a probability threshold of 0.5.

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3.2.Fully Convolutional Network

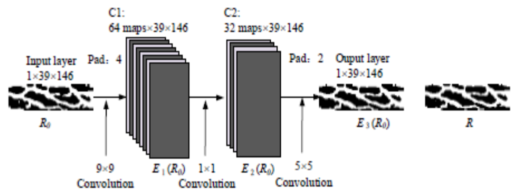

FIG 2:Architecture of FCN

we generate a corrupted image by randomly cropping some few pixels from the vein patterns. We provide to the FCN the corrupted image as input and the original image as output , and let the FCN learn how to recover the missing vein patterns, by learning an internal feature representation that minimizes the reconstruction error between the corrupted and original (ground truth) images. In the test phase, given a possibly corrupted finger-vein image R0, the FCN provides as outputthe finger-vein image with recovered missing patterns E3(R0). Both input and output images (layers) have 39 _ 146 = 5691 dimensions for database A and 50 _ 150 = 7500 dimensionsfor database B described in section V.In the first layer, the input image is transformed to n1 featuremaps by Eq.(3) which can be reformulated into a matrix formE1(R0) = max(0;W1 _ R0 + B1) (11)where E1 is a mapping function that extracts features from theinput image, and W1 and B1 represent the weight and bias. Here, W1 contains n1 kernels [w1 1;m1 ; w1 2;m1 ; :::; w1 n1;m1], wherem1 is the number of channels in the input image, and B1 is a vector [b11; b12 ; :::; b1 n1]. The first layer extracts a n1-dimensional feature for each input image. In the second layer, we map each of these n1-dimensionalvectors into an n2-dimensional one by the function E2: E2(R0) = max(0;W2 _ E1(R0) + B2) (12) where W2 corresponds to n2 kernels [w2 1;n1; w2 2;n1 ; :::; w2 n3]. The size of weight kernels in each layer is set to 9_9, 1_1 and 5_5, and the dimensions of the network layers are respectivelyn1 = 64, n2 = 32 and n3 = 1 as (the selection of FCN architecture is detailed in section V-C). We pad theoutput in each layer such that the reconstructed image and the Ground truth have the same size. All the weight matrices are updated by minimizing the loss function of reconstruction error, and then a end-to-end mapping function E is obtained to recover possibly missing vein patterns in the corrupted**.** This paper presents the work which simultaneously acquires the finger-vein and low-resolution finger images and that combines these two techniques which using a better score-level combination strategy. Here, analyzing the previous proposed finger-vein identification approaches and develop a new approach that describes it superiority over prior published efforts. In this thesis here develop and analyze the three new score-level combinations which are repeated line tracking, support vector machine and maximum curvature comparatively evaluate them with more popular score-level fusion approaches to ascertain their effectiveness in the proposed system.

Vein recognition technology however offers a promising solution to these challenges due the following features. (1) Its universality and uniqueness just as individuals have unique fingerprints so also they have unique finger vein image and most people remain unchanged despite ageing. (2) Detection methods for hand and finger vein do not have any known negative effects on body health. (3) Epidermis condition has no effect on vein detection result.

SVM stands for support vector machines it also known as support vector networks which are manage the learning models with associated learning algorithms that analyse the data and recognize patterns which are used for classification and regression analysis. There are properties of SVM: 1. Flexibility in choosing a similarity function. 2. Sparseness of solution when dealing with large data sets only support vectors are used to specify the separating hyper plane. 3. Ability to handle large feature spaces complexity does not depend on the dimensionality of the feature space. 4. Over fitting can be controlled by soft margin approach. 5. A simple convex optimization problem which is guaranteed to converge to a single global solution 6. Feature Selection.

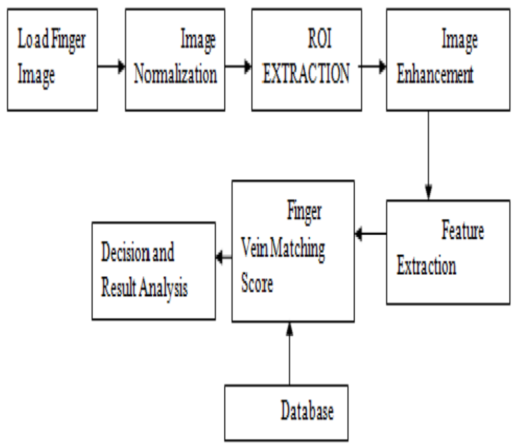

FIG3:block diagram of the proposed system

In this proposed work doing segmentation foreground pixel from background pixels by predicting the probability of the pixel belong to a vein pattern given limited knowledge.Recovering missing pattern using fully convolution network. The present study proposed an end-to-end finger-vein recognition system based on the and vein image extraction/matching is implemented on the k-edge subtraction is used to removal of background noise.a MATLAB application platform. Our system is suitable for mobile device because of its low computational complexity and low power consumption. As the finger-vein is a promising biometric pattern for personal identification in terms of its security and convenience. Also the vein is hidden inside the body and is mostly invisible to human eyes, so it is difficult to forge or steal. The non-invasive and contactless capture of finger-veins ensures both convenience and hygiene for the user, and is thus more acceptable. SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall.

IV.RESULT AND DISCUSSION

This section presents the results of the proposed work. The following figures show the result of the Enhancement of the Finger Vein recognition with segmentation and SVM. This technique gives better results as compared to previous techniques. After obtaining all the necessary terms Finger Vein Recognition , Segmentation and SVM for a number of images in our database; implemented the results in the final method. The proposed method is more accurate and assures quality of result. Human

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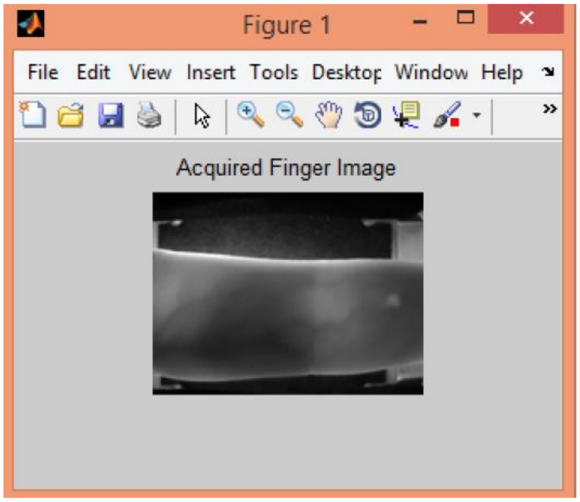
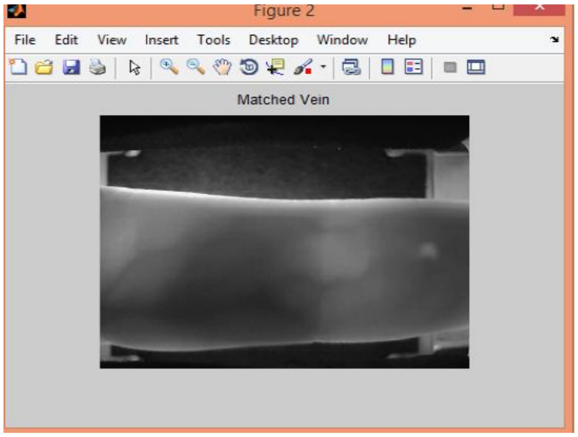
Identification algorithm Using Finger Vein which based on Automatic Trimap Generation, Repeated Line Tracking, Gabor and SVM is proposed. Algorithm which is fast and accurate and thus take less time as comparison to other technique. Inproposed algorithm consider some new parameters like PSNR, FAR, GAR and Accuracy, thus it is good in quality





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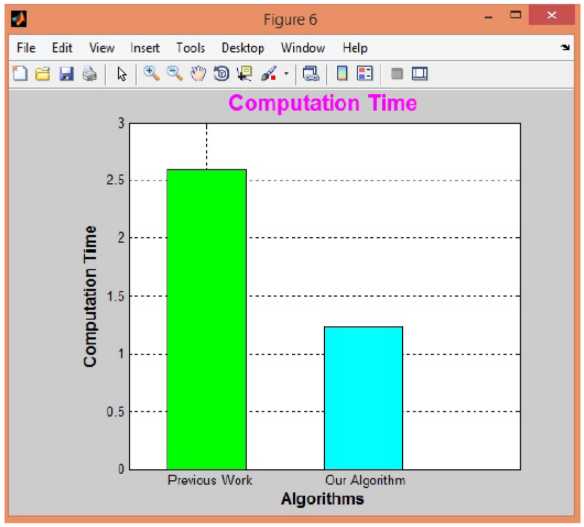

V.CONCOLUSION

Finger Vein is new biometric method which is increase day by day. As Finger vein identification uses the unique patterns of finger veins images to identify individuals at a high level of accuracy and security. The credibility of the finger vein authentication is higher. In this work, systematically develop a new approach for the finger vein feature extraction using Repeated Line tracking, Gabor filters and SVM is developed. The result comes after the combinations of these three methods are more accurate than the results of the individual method. The result comes for GAR and the FAR after comparing with the individual technique is more accurate. The GAR and FAR output for individual Repeated Line Tracking approach, Gabor and Matched filter methods after many results is very low but the combination of these three method increase the results accuracy to very high, which shows that the combination of these two method gives much better results as compared to the individual use of these methods. Using this algorithm the PSNR values also increases as compared with literature which provide high quality of work. The time taken in Enhancement and segmentation also reduces as compared with literature.

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