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Implementation of Weighted Fusion Algorithm for Palm Print Identification

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***Abstract*— Palm print identification is an important personal identification and authentication method. Palm is explained as the inner surface of hand from the wrist to the root of the figures. In this paper we develop the accurate personal identification by combining the left and right palm print images. Palm printing has gained the attention over several years from recent researches in multibiometrics. As the security system has very much important in several fields, it is very important to authenticate the users for any access. As many studies have been proposed but these researches did not explore the security issue in depth, so in this paper we established a framework in order to perform multibiometrics by combining left and right palm print images. The framework which we implemented here requires pre-processing to remove the noisy portions and to enhance the image, Gaussian filter for enhancing the image. In this, the image is subjected to binarization with an average threshold value. The ROI portion was extracted based on bounding box calculation. After extracting the ROI part, the image was in gray scale form. The gray scale image was converted into binary image. This process of conversion is known as binarization. We used canny edge detection technique for detecting the edges of the image. Morphological operation is used for expanding and reducing the shape of the image. Here we used morphological Opening, which remove the unwanted pixels (small objects) which are present in the image. Gabor filter is used for palm image feature extraction. The extracted features of the left and the right palm image are combined and stored in the feature database. This process was repeated for all the images present in the input database. After this training process gets over, we choose a single testing image each from right and left palm print folder respectively. If it was matched with the database, it results as genuine and if it was not matched, it results as fake. Thus recognition was achieved.**

***Keywords*— Palm printing, Gabor filter, Canny edge detection, Normalization and ROI extraction.**

I. INTRODUCTION

Important personal identification technique is palm print identification. It the palm print identification has capacity to achieve a high accuracy, since technique contains not only principle curves, wrinkles, rich texture and minuscule points, and also due to availability of rich information in palm print. Various palm print identification methods, such as coding based methods and principle curve method have been proposed in past years. Along with those methods one more method called subspace based methods in this method also Palm is defined as the inner surface of human hand from human wrist to the root of their fingers. Many other techniques are deployed for palm printing in that Representation Based Classification (RBC) method also shows good performance in this regard and also Scale Invariant Feature Transform (SIFT) which transforms image data into scale-invariant coordinates, are successfully introduced for the contactless palm print identification. A print is an impression made in or on a surface by pressure. A palm print is defined as the skin pattern of a palm, composed of the physical characteristics of skin pattern such as lines, points and texture. Palm print is rich in principal lines, wrinkles, ridges, singular points and minutiae points. Palm print has a much larger area than finger tip. As the security system has very much important in several fields, it is very important to authenticate the users for any access. As many studies have been proposed but these researches did not explore the security issue in depth, so in this paper we established a framework in order to perform multibiometrics by combining left and right palm print images. The authentication system consists of enrolment and verification stages. In enrolment stage, will consider the training samples and processed by pre-processing, feature extraction and modeling modules to produce the matching templates. Where as in verification, a query sample is also processed by preprocessing and feature extraction method and then is matched with reference templates to decide whether it is sample which we considered or not. A setup system consisting of a palm print based authentication system can work with multipurpose camera in an uncontrolled circumstances like mounted on a laptop, mobile device. Unlike earlier biometric systems, it does not require equipment and have attained higher accuracy value equivalent to fingerprint. We used SIFT and OLOF method, is an algorithm in palm print recognition to detect and describe local features in images.

Old multibiometrics methods treat different pattern independently. However, some special kinds of biometric traits have a similarity and these methods cannot exploit the similarity of different kinds of pattern. For example, the left and right palm print traits of the same subject can be viewed as this kind of special biometric traits owing to the similarity between them, which will be demonstrated later. However, there is almost no any attempt to explore the correlation between the left and right palm print and there is no "special" fusion method for this kind of biometric identification. This specialized algorithm carefully takes the nature of the left and right palm print images into consideration, it can properly examine the similarities between the left and right palm prints of the same object/human.

The framework which we implemented here will integrate three kinds of scores; these scores are generated from the left and right palm print images to do matching score level fusion.

First two kind of scores can be obtained from any other conventional methods easily but the third kind of score has to obtain using specialized algorithm, which takes the nature of the left and right palm print images into consideration, it can properly exploit the similarity of the left and right palm prints of the same subject. Moreover, the proposed weighted fusion scheme allowed perfect identification performance to be obtained in comparison with previous palm print identification methods. Moreover, the proposed specialized fusion scheme allowed perfect identification performance to be obtained in comparison with old conventional palm print identification methods.

II. Related Work

Rowe et al. [1] has proposed a multispectral whole-hand biometric system. In this their main objective is to collect palm print information with clear fingerprint features, and pre-processing and done with the imaging resolution was set to 500 dpi. However, the low speed of feature extraction and feature matching makes it unsuitable for real-time applications. So less accuracy in the proposed system there can be enhancement of system can be achieved by applying many other palm print techniques. s. Hao et al. [2] has developed contact-free multispectral palm sensor architecture for identifying the palm printing for security and authentification. However, the image quality is very much limited, so recognition accuracy is not so high. Overall, multispectral palm print scanning is a relatively new topic, and the aforementioned works stand for the state-of-the-art work. So less accuracy in the proposed system there can be enhancement of system can be achieved by applying many other palm print techniques. Qiushi Zhao et al. [3] have proposed SIFT-based Image Alignment for Contactless Palm print Verification. In this paper they have aiming at solving security based problems, they proposed a contactless palm print recognition method with a precise palm print image alignment. The original contactless palm print images are firstly aligned using a projective transformation model that estimated from matched SIFT feature points. From the obtained images, an exact palm print feature representation method, the competitive code, is extracted and matched. Finally, matching scores of both SIFT and competitive code is fused to further improve the accuracy. Experiments on a public contactless palm print database show that after the image alignment, the verification accuracy of competitive code has increased dramatically, and the result is further enhanced by fusing the matching scores of competitive code and SIFT features. Feng Yue et al. [4] have proposed FCM-based Orientation Selection for Competitive Coding-based Palm print Recognition. In this paper they concentrated on the security issues and tried to overcome all the issues, in this prospective they used statistical orientation distribution and the orientation separation principle and modified fuzzy C-means cluster algorithm to determine the orientations of filters. This method achieves higher verification accuracy while compared with that of the original competitive code and several state-of-the-art methods. Considering both the computational complexity and the verification accuracy, six filters would be the optimal choice for proposed method.
Likforman-Sulem et al. [5] used multispectral images in a multimodal authentication system; however, their system used an optical desktop scanner and a thermal camera, which make the system very costly. The imaging resolution is also too high (600 dpi, the FBI fingerprint standard) to meet the real-time requirement in practical biometric systems.

III. Methodology

Figure 1 represents the proposed architecture. The architecture first starts working for the left palm print images and same procedure has to fallow for right palm print images and utilizes a palm print identification method to calculate the scores of the test samples with respect to each class. In-order to remove the noisy portions and to enhance the image, pre-processing is needed. Here, we are using Gaussian filter for enhancing the image. Since, Gaussian filter is well known for smoothening and sharpening the image, we used this filter and normalization is a process that changes the range of pixel intensity values. In this, the image is subjected to binarization with an average threshold value. Eventhough after image enhancement, some distortions are present in the background portions of the image. So it is necessary to remove the unwanted portions of the image and to extract the palm region alone. This process of extracting the important regions is known as Region of Interest (ROI) Extraction. The ROI portion was extracted based on bounding box calculation. After extracting the ROI part, the image was in gray scale form. The gray scale image was converted into binary image. This process of conversion is known as binarization. We use canny edge detection technique for detecting the edges of the image. Morphological operation is used for expanding and reducing the shape of the image. Here we used morphological Opening, which remove the unwanted pixels (small objects) which are present in the image. Gabor filter is used for palm image feature extraction. The extracted features of the left and the right palm image are combined and stored in the feature database. This process was repeated for all the images present in the input database. After this training process gets over, we choose a single testing image each from right and left palm print folder respectively. If it was matched with the database, it results as genuine and if it was not matched, it results as fake. Thus recognition was achieved.

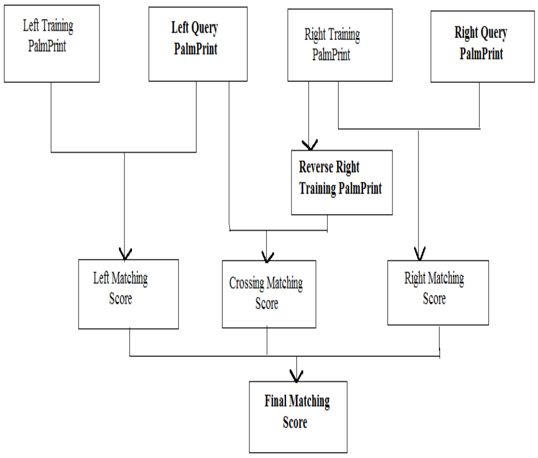

Figure 1: Block Diagram of Proposed System.

A. PREPROCESSING

The left and right palm images of the human are given as the input. There will be a lot of distortion and noise in the images since the images are taken from the camera; In-order to remove the noisy portions and to enhance the image, preprocessing is needed. Here, we are using Gaussian filter for enhancing the image. Since, Gaussian filter is well known for smoothening and sharpening the image, we used this filter. The output image is the enhanced image. Normalization is a process that changes the range of pixel intensity values. In this, the image is subjected to binarization with an average threshold value, which can be explained as, it is a process where each pixel in an image is converted into one bit and we have to assign the value as '1' or '0' depending upon the mean value of all the pixel. If greater then mean value then its '1' otherwise its '0'. Image binarization converts an image of up to 256 gray levels to a black and white image. Main intension is to convert image into gray scale image. Simple way to use image binarization is to select a threshold value, and classify all pixels with values above this threshold as white, and all other pixels as black. The problem then is how to select the correct threshold. In many cases, finding one threshold compatible to the entire image is very difficult, and in many cases even impossible. Therefore, adaptive image binarization is needed where an optimal threshold is chosen for each image area. It is very necessary to estimate the orientation and block direction of the considered enhanced and normalized image. The direction for each block of the fingerprint image with W x W in size is estimated be using the fallowing algorithm,

1. Two Sobel filters are used to estimate and calculate the gradient values along x-direction (g_x) and y-direction (g_y) for each pixel of the block.

2. For each block, following formula is used to get the Least Square approximation of the considered block direction.

$$t_g 2\beta = 2\sum\sum \frac{g_x * g_y}{\sum\sum(g_x^2 * g_y^2)} \quad (1)$$

After the estimation of each block direction, those blocks without significant information on ridges and furrows are discarded based on the following formulas:

$$E = \frac{\{2\sum\sum(g_x * g_y) + (g_x^2 - g_y^2)\}}{w * w * \sum\sum(g_x^2 + g_y^2)} \quad (2)$$

For each block, if its certainty level E is below a threshold, then the block is regarded as a background block. Even-though after image enhancement and orientation estimation, some distortions are present in the background portions of the image. So it is necessary to remove the unwanted portions of the image and to extract the palm region alone. This process of extracting the foreground regions is known as Region of Interest (ROI) Extraction. The ROI portion was extracted based on bounding box calculation.

B. CANNY EDGE DETECTION ALGORITHM

Canny edge detector is widely considered to be the standard edge detection algorithm in the industry. There are several steps are to be fallowed in the canny edge detector, firstly we have to smoothen the image with a two dimension Gaussian, next take the gradient of a considered image, then suppression is done through non-maximal, then edge threshold is calculated. The next step is to extract moving edges from sequential video frames and process the resulting edge information to obtain quantitative geometric measurements of passing vehicles. We are comparing and calculating vehicle density by using these two different edge techniques. The edges are detected by the canny edge algorithm.

Using the gradient kernel approach image gradient magnitude is calculated in horizontal direction. G_x and vertical Direction G_y for each pixel. And the direction of the pixel is measured by

$$\theta = arc\tan\left(\frac{G_y}{G_x}\right) \quad (3)$$

Threshold values such at the higher threshold value (HIV) and lower threshold value (LTV) are selected from the histogram of the image in order to detect the edges. After that verification is implemented by using these threshold values against each pixel respectively by using Non maxima suppression as given below.

1. The gradient of the pixel is greater than the HIV the sense that pixel is taken as edge pixel.

2. If the gradient is lie between high and lower threshold value in the sense, that value is also consider as edge pixel.

3. If the gradient value is lower than the LTV in the sense that is declared as non edge pixel.

This lower and higher threshold values are verified by the observation of the experiments. These two threshold values are used for to detect large edges and to find the small edges. After edge detection of input image, the input images of left and right palm print should be converted to the binary image consists of only 1's and 0's (for black and white), the edge of the image which is directly extracted by the morphological basic operations from the input images. Morphological operation is used for expanding and reducing the shape of the image. Here we used morphological Opening, which remove the unwanted pixels (small objects) which are present in the image.

C. GABOR FILTER FOR FEATURE EXTRACTION

For extracting the texture features, Gabor wavelet transformation is used. Gabor filters are directly related to Gabor wavelets; it has some attractive mathematical and biological properties and has been used frequently on researches of image processing. Gabor functions provide the optimal resolution in both the time and frequency domains, and the Gabor wavelet transform seems to be the optimal basis to extract local features for several reasons, they are Biological motivation and Mathematical and empirical motivation.

Gabor function is given as

$$\varphi(x,y) = \frac{f^2}{\pi\gamma\eta}\exp\left(-\left(\frac{f^2}{\gamma^2}X_r^2 + \frac{f^2}{\eta^2}y_r^2\right)\right)(\exp(j2\pi x_r) - k \qquad (4)$$

where K is an offset parameter. since they can be designed for number of dilations and rotations. However, in general, expansion is not applied for Gabor wavelets, since this requires computation of biorthogonal wavelets, which may be very time consuming. Therefore, usually, a filter bank consisting of Gabor filters with various scales and rotations is created. A Gabor filter can be viewed as a sinusoidal plane of particular frequency and orientation, modulated by a Gaussian envelope.

$$G(x,y)=s(x,y)g(x,y) \qquad (5)$$

where s(x,y) is complex sinusoid and g(x,y) is 2D gaussian envelope

$$s(x,y)=\exp[-j2\Pi(\mu_0 x+\upsilon_0 y)] \qquad (6)$$

$$g(x,y) = \frac{1}{\sqrt{2\pi}\sigma_x\sigma_y}\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)\right] \qquad (7)$$

σ_x and σ_y characterize the spatial extent and bandwidth of along the respective axes, u_0 and υ_0 are the shifting frequency parameters in the frequency domain. Using G(x, y) as the mother wavelet, the Gabor wavelets, a class of self-similar functions can be obtained by appropriate dilations and rotations of G(x,y) through:

$G_{m,n}(x,y) = a^{-m}G(x',y')$,

where $x'=a^{-m}(x\cos\square+y\sin\square)=a^{-m}(x\sin\square+y\cos\square)$,

$y'=a^{-m}(x\sin\square+y\cos\square)$, $a>1$, $\square=\frac{n\pi}{O}$, $m=1 \ldots S$ $n= 1 \ldots O$.

O indicates the number of orientations, S the number of scales in the multi resolution decomposition and a is the scaling factor between different scales. These parameters can be set according to reduce the redundant information (caused by the Non orthogonality of the Gabor wavelets) in the filtered images.

Given an image I(x, y), the Gabor transform with orientation n and m scale can be computed as resolution decomposition and a is the scaling factor between different scales. These parameters can be set according to reduce the redundant information (caused by the Non orthogonality of the Gabor wavelets) in the filtered images.

Given an image I(x, y), the Gabor transform with orientation n and m scale can be computed as

$$F_{m,n}(x,y) = \int I(x1,y1)\ G^*_{m,n}(x-x_1,-y_1)\,dx_1dy_1 \quad (8)$$

Where indicates the complex conjugate. In our work, we set the Gabor filter to have S=4 scale levels and O=6 orientations, Gives the examples of the extracted Gabor features using the designed filter bank on T1, PD, T2 and FA images, respectively. As we can see, on different locations, scales and orientations, we need Gabor features from different modalities to best delineate the underlying structure. For instance, in the corpus callous, since it is mainly white matter, Gabor features from FA image (computed from DTI) is expected to give stronger response.

IV. IMPLEMENTATION

Modules description

1. Similarity between the Left and Right Palmprints
   - The illustration of the correlation between the left and right palmprints is presented in this module.

2. Score level fusion Framework
   - The framework first works for the left palmprint images and uses a palmprint identification method to calculate the scores of the test sample with respect to each class.
   - Then it applies the palmprint identification method to the right palmprint images to calculate the score of the test sample with respect to each class.

- After the crossing matching score of the left palmprint image for testing with respect to the reverse right palmprint images of each class is obtained, the proposed framework performs matching score level fusion to integrate these three scores to obtain the identification result.

3. Matching Score Level Fusion
   - The final decision making is based on three kinds of information: the left palmprint, the right prlmprint and the correlation between the left and right palmprint.
   - In score level, the weight-sum scorelevel fusion strategy is effective for component classifier combination to improve the performance of biometric identification. The strength of individual matchers can be highlighted by assigning a weight to each matching score.
   - Consequently, the weight-sum matching score level fusion is preferable due to the ease in combining three kinds of matching scores of the proposed method.
   - The first and second matching scores are obtained from the left and right palmprint, respectively.
   - The third kind of score is calculated based on the crossing matching between the left and right palmprint.

4. Score level and Decision level Fusion
   - Given a set of component matching scores, and a set of score-level fusion methods.
   - (Training) Derive individual ROCs from the component matching scores and the score-level fused matching scores. Fuse all the ROCs under the fusion framework by the AND rule or OR rule, and obtain the optimal combination of operation points.
   - Obtain the thresholds corresponding to those optimized operation points.
   - (Testing) Apply the trained thresholds on the component matching scores the score-level fused matching scores, and fuse the decisions by the AND rule or OR rule as the final decision.

V. RESULTS

After implementing the proposed system on Matlab platform, the results obtained are as follows:

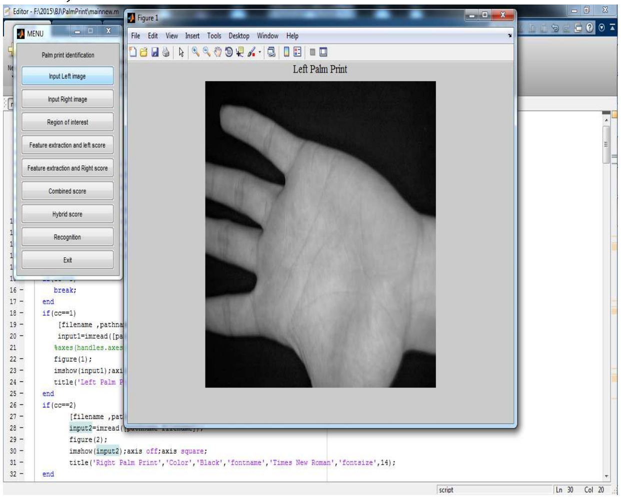

Fig.2 Input left palm image

In this image the sample of left palm print is passed as an input to the program. Here the user can select the input image dynamically with the help of dialogue box.

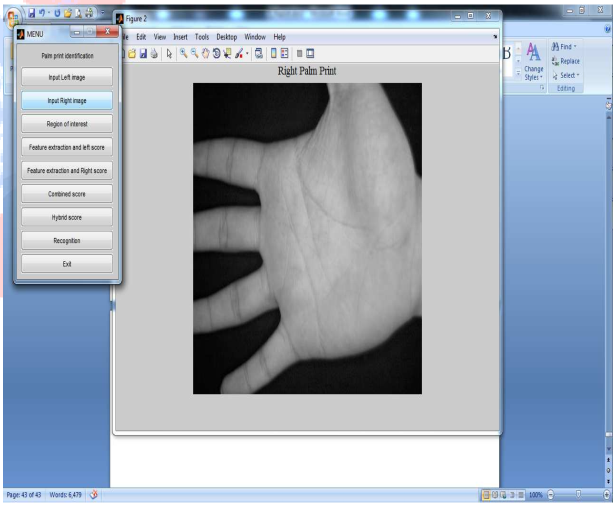

Fig.3 Input right palm image

Similarly we are passing the sample right palm image as an input as shown in figure 3.

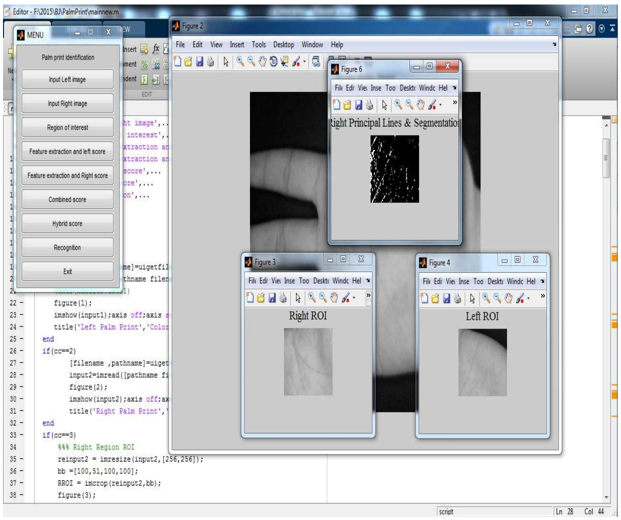

Fig.4 Results of ROI and feature extraction

In this image we can able to see the Region of interest commonly known as ROI extracted for the both samples i.e. for left palmprint and also for right palm print. And image also displaying the feature like principle line of corresponding samples.

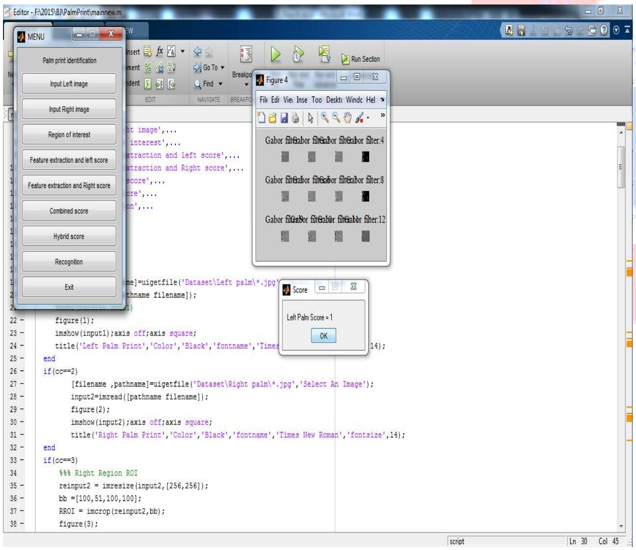

Fig.5 Left palm Score result

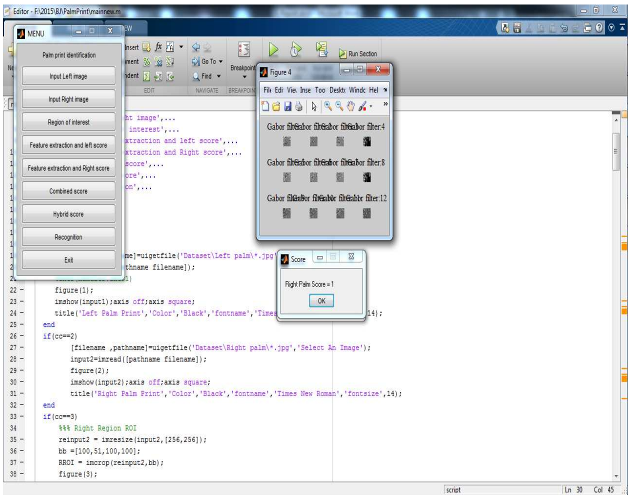

Fig.6 Right palm result

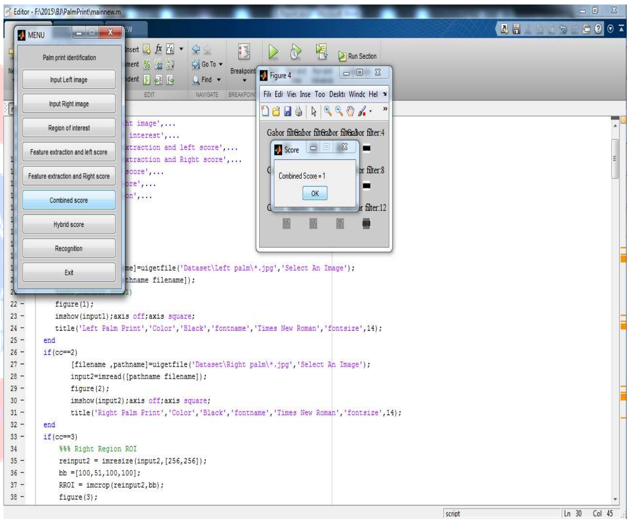

Fig.7 Combined score result

In this image (Fig.7) it is displayed combined result of the operation, i.e. score value got by applying weighted fusion technique.

VI. Conclusion

This study shows that the left and right palmprint images of the same subject are somewhat similar. The use of this kind of similarity for the performance improvement of palmprint identification has been explored in this paper. The proposed method carefully takes the nature of the left and right palmprint images into account, and designs an algorithm to evaluate the similarity between them. Moreover, by employing this similarity, the proposed weighted fusion scheme uses a method to integrate the three kinds of scores generated from the left and right palmprint images. Extensive experiments demonstrate that the proposed framework obtains very high accuracy and the use of the similarity score between the left and right palmprint leads to important improvement in the accuracy. This work also seems to be helpful in motivating people to explore potential relation between the traits of other bimodal biometrics issues.

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