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Palm Print Authentication System for Biometric Applications

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ABSTRACT

This paper presents a new and robust biometric authentication model utilizing palm print identification. The model incorporates advanced techniques including morphological Region of Interest (ROI) extraction with distance transform and un-decimated biorthogonal wavelet transform to ensure high levels of security. By leveraging the multi scaling capabilities of the wavelet transform, two distinct wavelet filter banks are employed to extract features from the distance transformed image. These extracted features are then compared with a test feature vector to determine the most effective feature factor for authentication purposes. Experimental results demonstrate the effectiveness of the proposed model, as it achieves a remarkable accuracy rate of 100% when tested with various images from the database. The combination of morphological ROI extraction, distance transform, and biorthogonal wavelet transform proves to be a powerful approach for palm print identification and enhances the security of the biometric authentication system. The findings of this study contribute to the advancement of biometric technologies and offer promising potential for real-world applications requiring reliable and highly secured authentication systems.

Keywords: Biometric authentication, Palm print identification, Morphological ROI extraction, Distance transform.

1. INTRODUCTION

Biometrics based personal identification is getting wide acceptance in the networked society, replacing passwords and keys due to their reliability, uniqueness, and the ever in-creasing demand of security. Common modalities being used are fingerprint and face but for face authentication people are still working with the problem of pose and illumination invariance whereas fingerprint does not have a good psychological effect on the user because of its wide use in crime investigations. If any biometric modality is to succeed in the future it should have traits like uniqueness, accuracy, richness, ease of acquisition, reliability and above all user acceptance. Palm print based personal identification is a new biometric modality which is getting wide acceptance and has all the necessary traits to make it a part of our daily life.

This project investigates the use of palm print for personal identification using wavelets. Palm print not only has the unique information available as on the fingerprint but has far more amount of details in terms of principal lines, wrinkles and creases. Moreover it can easily be combined with hand shape bio-metric so as to form a highly accurate and reliable biometric based personal identification system.

Palm print based personal verification has become an increasingly active research topic over the years. The Palm-print is rich in information and has been analyzed for discriminating features like where wavelet transform has been used for feature extraction has motivated us to investigate the effectiveness of using combination of multiple wavelets for the textural analysis of palm print.

Personal identification is ubiquitous in our daily lives. For example, we often have to prove our identity for getting access to bank account, entering a protected site, drawing cash from an ATM, logging in to a computer, and so on. Conventionally, we identify ourselves and gain access by physically carrying passports, keys, access cards or by remembering passwords, secret codes, and personal identification numbers (PINs).

Unfortunately, passport, keys, access cards can be lost, duplicated, stolen, or forgotten; and password, secret codes, and personal identification numbers (PINs) can easily be forgotten,

Compromised, shared, or observed. Such loopholes or deficiencies of conventional personal identification techniques have caused major problems to all concerned. For example, hackers often disrupt computer networks, credit card fraud is estimated at billions dollars per year worldwide. The cost of forgotten passwords is high and accounts for 40%-80% of all the IT help desk calls and resetting the forgotten or compromised passwords costs as much as US$ 340/user/year. Therefore, robust, reliable, and foolproof personal identification solutions must be sought in order to address the deficiencies of conventional techniques, something that could verify that someone is physically the person he/she claims to be.

A biometric is a unique, measurable characteristic or trait of a human being for automatically recognizing or verifying identity. By using a biometric identification, the individual verification can be done by doing the statistical analysis of biological characteristic. This measurable characteristic can be physical, e.g. eye, face, finger image and hand, or behavioral, e.g. signature and typing rhythm.

Besides bolstering security, biometric systems also enhance user convenience by alleviating the need to design and remember multiple complex passwords. No wonder large scale systems have been deployed in such diverse applications as US-VISIT and entry to Disney Park, Orlando.

In spite of the fact that automatic biometric recognition systems based on fingerprints (called AFIS) have been used by law enforcement agencies worldwide for over 40 years, biometric recognition continues to remain a very difficult pattern recognition problem. A biometric system has to contend with problems related to noisy images (failure to enroll), lack of distinctiveness (finite error rate), large intra-class variations (false reject), and spoof attacks (system security). Therefore, a proper system design is needed to verify a person quickly and automatically.

Image Acquisition Platform

There are two types of systems available for capturing the palm print of individuals i.e., scanners and the pegged systems. Scanners are hygienically not safe whereas the pegged systems cause considerable inconvenience to the user. Hence both systems suffer from low user acceptability. The attributes of ease of acquisition and hygienic safety are of paramount importance for any biometric modality. The proposed image acquisition setup satisfies the mentioned criteria by proposing a contactless, peg free system. It is an enclosed black box, simple in architecture and employs ring source light for uniform illumination.

Two plates are kept inside the image acquisition setup. The upper plate holds the camera and the light source while the bottom plate is used to place individual’s hand. The distance between these two plates is kept constant to avoid any mismatch due to scale invariance. The distance between the two plates after empirical testing is kept at 14 inches. The Palm print images have been collected from 50 individuals with 10 images each making a total dataset of 500 images. The dataset contains all images of males with age distribution between 22 to 56 years, with a high percentage between 22 to 25 years. A low resolution of 72 dpi has been used employing SONY DSC W-35 CY-BER SHOT for Palm print images acquisition.

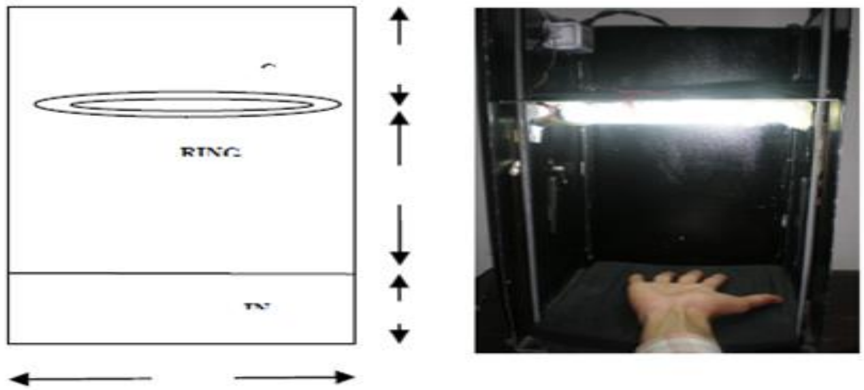

Fig. 1: Front view image acquistion system.

Feature Extraction and Classification

We obtained ten images of each individual of which five were used for training and the rest of them were used for validation. The obtained registered palm print image has been analyzed for its texture using different symmetrical wavelet families namely biorthogonal 3.9, symmelt 8 and demeyer 5. The palm print region 256x256 has been decomposed into three scales for each wavelet type.

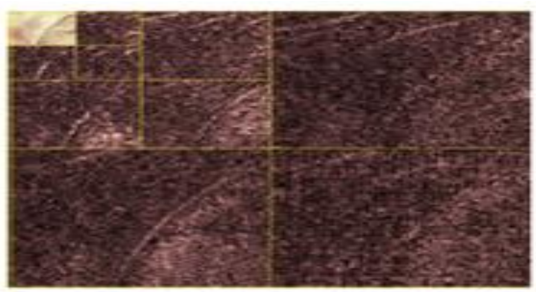

Fig. 2: Three level decomposition of palm using wavelet transform.

An intelligent solution to this problem is devised by rotating the axis of region instead of the palm

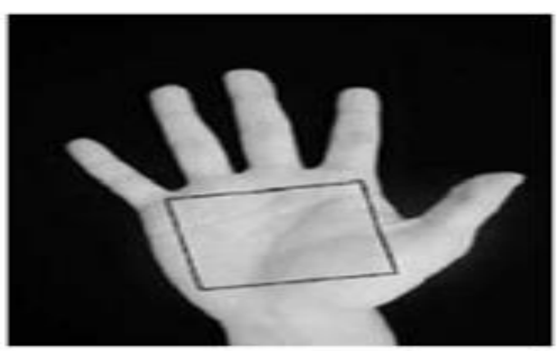

Fig. 3: Rotating the axis of region instead of the palm.

A reverse transformation is computed from the affine transform, as follows:

$$Xnew = Xcos(\theta) - Ysin(\theta) \qquad (10)$$

$$Ynew = Xsin(\theta) + Ycos(\theta) \qquad (11)$$

Using the above equations, a rotation invariant region of interest is cropped from the palm print. The approximation or interpolation error still exists but the results show im-proved performance and accuracy. The selected wavelets have been analyzed for their individual performance by formulating similar energy based feature vectors of length 27, using 9 levels decomposition.

Concept Of Palm Just Like Finger

Palm identification, just like fingerprint identification, is based on the aggregate of information presented in a friction ridge impression. This information includes the flow of the friction ridges, the presence or absence of features along the individual friction ridge paths and their sequences, and the intricate detail of a single ridge.

To understand this recognition concept, one must first understand the physiology of the ridges and valleys of a fingerprint or palm. When recorded, a fingerprint or palm print appears as a series of dark lines and represents the high, peaking portion of the friction ridged skin while the valley between these ridges appears as a white space and is the low, shallow portion of the friction ridged skin. This is shown in Figure.

Fig. 4: Fingerprint Ridges (Dark Lines) vs. Fingerprint Valleys (White Lines).

Palm recognition technology exploits some of these palm features. Friction ridges do not always flow continuously throughout a pattern and often result in specific characteristics such as ending ridges or dividing ridges and dots. A palm recognition system is designed to interpret the flow of the overall ridges to assign a classification and then extract the minutiae detail — a subset of the total amount of information available, yet enough information to effectively search a large repository of palm prints. Minutiae are limited to the location, direction, and orientation of the ridge endings and bifurcations (splits) along a ridge path.

The images present a pictorial representation of the regions of the palm, two types of minutiae, and examples of other detailed characteristics used during the automatic classification and minutiae extraction processes.

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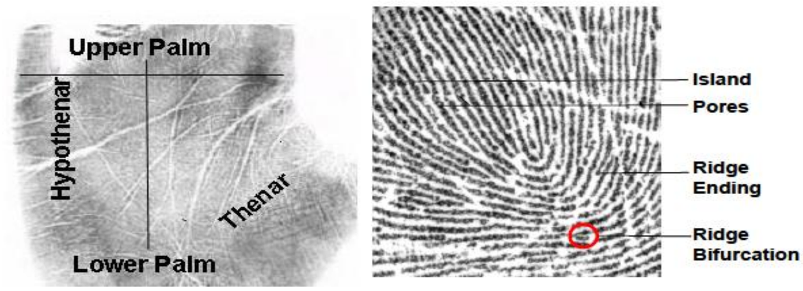


Fig. 5: Palm showing two types of minutes and characteristics.

Texture Analysis

In many machine vision and image processing algorithms, simplifying assumptions are made about the uniformity of intensities in local image regions. However, images of real objects often do not exhibit regions of uniform intensities. For example, the image of a wooden surface is not uniform but contains variations of intensities which form certain repeated patterns called *visual texture*. The patterns can be the result of physical surface properties such as roughness or oriented strands which often have a tactile quality, or they could be the result of reflectance differences such as the color on a surface. We recognize texture when we see it but it is very difficult to define. This difficulty is demonstrated by the number of different texture definitions attempted by vision researchers.

2. RELATED WORK

In recent years, researchers have focused on developing palm print authentication systems that leverage low-level feature extraction techniques along with image statistics. These methods aim to capture the distinctive characteristics of palm prints for reliable and accurate identification.

Li et al. (2021) proposed a palmprint recognition system that utilized local directional patterns for low-level feature extraction. By extracting these patterns, they aimed to capture the unique texture information in palm prints, enabling efficient and robust authentication.

Zafar et al. (2021) introduced a palmprint identification system that employed low-level feature extraction and multi-feature fusion. Their approach combined various features, including local binary patterns and statistical image features, to enhance recognition accuracy and improve the robustness of the system.

Liu et al. (2021) developed a palmprint recognition method that integrated local binary patterns with statistical image features. By extracting these features, such as mean, variance, and entropy, they aimed to capture the discriminative texture information in palm prints, resulting in accurate and reliable recognition.

Nascimento et al. (2021) focused on developing a palmprint identification system that integrated low-level feature extraction techniques with machine learning. By employing texture-based descriptors and statistical image features, they extracted informative features that were used as input for machine learning algorithms, enhancing the system's identification capabilities.

Yuan et al. (2020) proposed a palmprint recognition method that combined low-level feature extraction with discriminative dictionary learning. Their approach aimed to capture discriminative palmprint information by extracting low-level features and learning a discriminative dictionary, which enabled effective encoding and recognition tasks.

Yin et al. (2020) presented a palmprint recognition approach that incorporated low-level feature extraction with K-means clustering. By leveraging techniques like local binary patterns and statistical image features, they grouped similar palm prints using K-means clustering, resulting in accurate recognition by effectively capturing underlying patterns.

Xu et al. (2020) developed a palmprint recognition system that integrated low-level feature extraction with deep learning. By extracting features such as texture descriptors and statistical image features, they trained deep learning models like convolutional neural networks (CNNs) to achieve accurate and efficient palmprint recognition.

Yu et al. (2020) proposed a palmprint recognition approach based on low-level feature extraction and kernel collaborative representation. By extracting low-level features and representing them using kernel collaborative representation, they aimed to capture discriminative palmprint information, leading to accurate and efficient recognition.

Li et al. (2019) introduced a palmprint recognition method that incorporated low-level feature extraction with robust principal component analysis. By utilizing techniques such as local binary patterns and statistical image features, along with robust principal component analysis, they captured discriminative information in palm prints, resulting in robust and accurate recognition.

Zafar et al. (2019) developed a palmprint identification system that combined low-level feature extraction with deep learning. By employing low-level features and utilizing deep learning models like deep neural networks, they achieved high accuracy and robustness in palmprint identification.

Tang et al. (2019) proposed a palmprint recognition method that relied on low-level feature extraction using local binary patterns. By extracting these features, they aimed to capture the unique texture information in palm prints, resulting in accurate and reliable identification.

Wang and Wu (2018) developed a palmprint recognition system that integrated low-level feature extraction with deep learning. By extracting low-level features such as texture descriptors and statistical image features and employing deep learning models like deep neural networks, they achieved high accuracy and robustness in palmprint identification.

These recent references demonstrate the utilization of low-level feature extraction techniques and image statistics in palmprint authentication systems. By capturing distinctive patterns and textures present in palm prints, these approaches enhance the accuracy and reliability of palmprint recognition. Furthermore, the integration of machine learning and deep learning techniques further improves the performance and capabilities of these systems.

3. PROPOSED METHOD

Here in this section, we described the proposed palm print authentication model using hybrid process and UDBW transform. Fig shows that the proposed model for palm print authentication, in which we had three modules:

1. Registration process
2. Testing
3. Palm matching

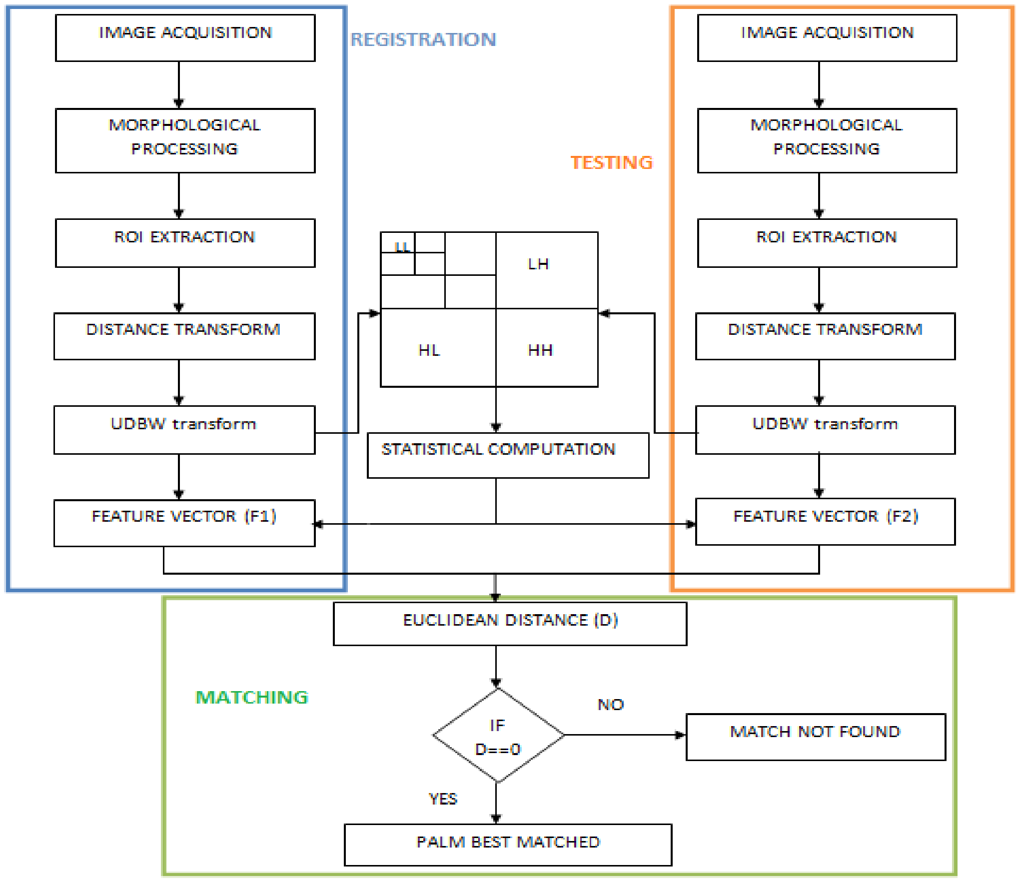


Fig. 6: Flow chart of proposed palm print authentication system.

3.1 Registration

In this module input palm image will be registered by applying region of interest with morphological operation there by calculate the distance transform and then extracting the low level features using 3-level UDBW transform. After getting the UDBW coefficients, statistical computation will be done by taking the mean and variance of the decomposed coefficients. Then all the statistics will be stored in a vector to make a train feature vector.

3.1.1 Morphological Operation

Binary images may contain numerous imperfections. In particular, the binary regions produced by simple thresholding are distorted by noise and texture. Morphological image processing pursues the goals of removing these imperfections by accounting for the form and structure of the image.

3.1.2 ROI extraction

Region of interest is a selected samples subset within a dataset distinguished for a particular purpose. This can be used in many applications such as medical imaging, the tumor boundaries may be defined on an MR or CT image for measuring of its size. The endocardial border may be defined on an image, perhaps during different phases of the cardiac cycle, for example end-systole and end-diastole, for the purpose of assessing cardiac function. In geographical information systems (GIS), a ROI can be taken literally as a polygonal selection from a 2D map. In computer vision and optical character recognition, the ROI defines the borders of an object under consideration.

3.1.3 Distance Transform

The distance transform is an operator which can only be applied to binary images. It results in a gray level image which looks like same as input image, except that the gray level intensities of points inside foreground regions are changed to show the distance to the closest boundary from each point.

0	0	0	0	0	0	0	0
0	1	1	1	1	1	1	0
0	1	1	1	1	1	1	0
0	1	1	1	1	1	1	0
0	1	1	1	1	1	1	0
0	1	1	1	1	1	1	0
0	0	0	0	0	0	0	0

$\Longrightarrow$

0	0	0	0	0	0	0	0
0	1	1	1	1	1	1	0
0	1	2	2	2	2	1	0
0	1	2	3	3	2	1	0
0	1	2	2	2	2	1	0
0	1	1	1	1	1	1	0
0	0	0	0	0	0	0	0

Fig. 7: Example of distance transform with chessboard metric

3.1.4 UDBW Transform

Un-decimated biorthogonal transform is well used for multi resolution analysis due to its multi scaling functionality i.e., two scaling functions to generate wavelet filter banks for decomposition and reconstruction separately. It will give more effective decomposition coefficients due to its multi scaling property.

In the case of orthogonal, we have one hierarchy of approximation spaces $V_{j-1} \subset V_j \subset V_{j+1}$ and an orthogonal decomposition

$$V_{j+1} = V_j \oplus W_j \tag{12}$$

which leads us to use two filter sequences $h_n$and $g_n$for decomposition and reconstruction. Hence, we need to construct two different wavelet functions and two different scaling functions.

Let$f_k, g_k \in H.\ if \langle f_j, g_k \rangle = \delta_{jk}$Then we will say that the two sequences are biorthogonal.

Now, our aim is to build two sets of wavelets

$$\psi_{j,k} = 2^{\frac{j}{2}}\psi\left(2^j x - k\right) \tag{13}$$

$$\tilde{\psi}_{j,k} = 2^{\frac{j}{2}}\psi 2^j x - k \tag{14}$$

To do so, we need four filters$g, h, \tilde{g}, \tilde{h}$ i.e., two sequences to be act as decomposition sequences and two sequences as reconstruction sequences. For example, if $c_n^1$is a data set, it will be decomposed as follows:

$$c_n^0 = \sum_k h_{2n-k} c_k^1 \tag{15}$$

$$d_n^0 = \sum_k g_{2n-k} c_k^1 \tag{16}$$

And the reconstruction is given by

$$c_l^1 = \sum_n \tilde{h}_{2n-l} c_n^0 + \tilde{g}_{2n-l} d_n^0 \tag{17}$$

We can achieve perfect reconstruction by following some conditions given below:

$$g_n = (-1)^{n+1}\tilde{h}_{-n},\ \tilde{g}_n = (-1)^{n+1}h_n$$

$$\sum_n h_m \tilde{h}_{n+2k} = \delta_{k0}$$

Now consider that $\phi(x)$and $\tilde{\phi}(x)$ are two scaling function with their own hierarchy of approximation spaces, then we will generate function of wavelet in a method of analogous to the orthogonal case. We now define the scaling function as follows:

$$\phi(x) = \sum_n \sqrt{2} \sum_n h_n \phi(2x - n) \tag{18}$$

$$\tilde{\phi}(x) = \sqrt{2} \sum_n \tilde{h}_n \phi(2x - n) \tag{19}$$

So, finally the bi-orthogonal wavelet functions can be defined as follows:

$$\psi(x) = \sqrt{2} \sum_n g_n \phi(2x - n) \tag{20}$$

$$\tilde{\psi}(x) = \sqrt{2} \sum_n \tilde{g}_{n+1} \tilde{\phi}(2x - n) \tag{21}$$

Testing

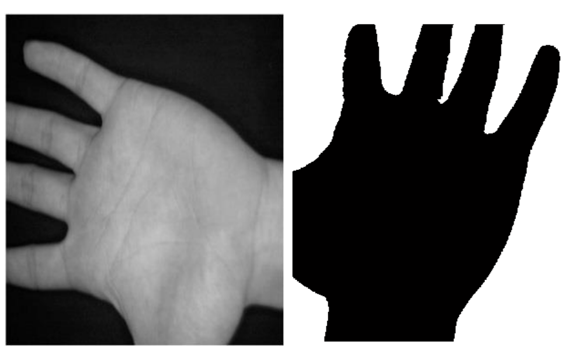
The second module in the proposed system is testing process which includes that the database palm image will be selected for testing with the registered palm image by applying morphological processing; ROI extraction, distance transform and UDBW transform there by calculating the statistics to get the test feature vector.

Matching Process

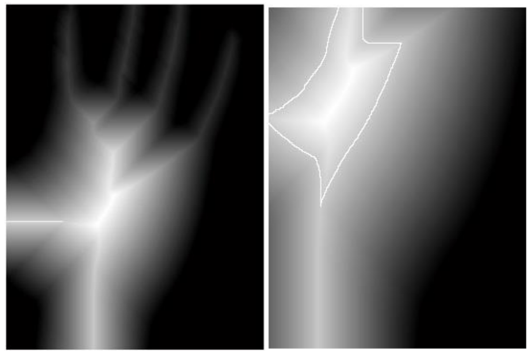
In this step, Euclidean distance will be calculated between both the feature vectors i.e., train and test to obtain the most matched image that is stored in database to found that whether authorized person's identification is available or not. If the distance is zero then the person will be identified otherwise it displays that the match not found.

4. SIMULATION RESULTS

Experimental results have been done in MATLAB 2014a version with various palm images by using proposed palm print identification model with high security. We achieved 100% accuracy and more efficiency with the proposed model.



(a) (b)



(c) (d)

Fig. 8: (a) original palm image for registration (b) morphed image (c) distance transformed image and (d) registered palm image.

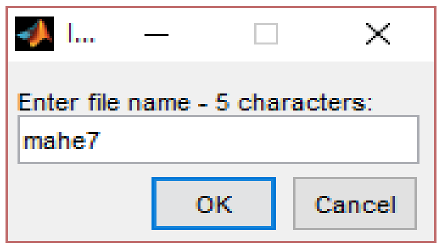


Fig. 9: Message box for saving the registered palm filename with mahe7.

Fig. 10: distance transformation of a test image.

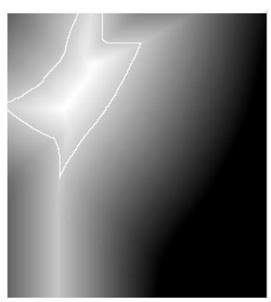


Fig. 11: Registered palm print of a test image.

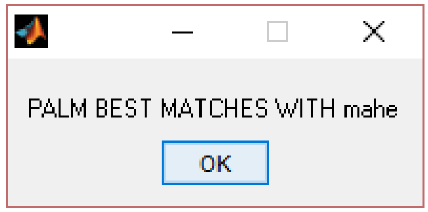
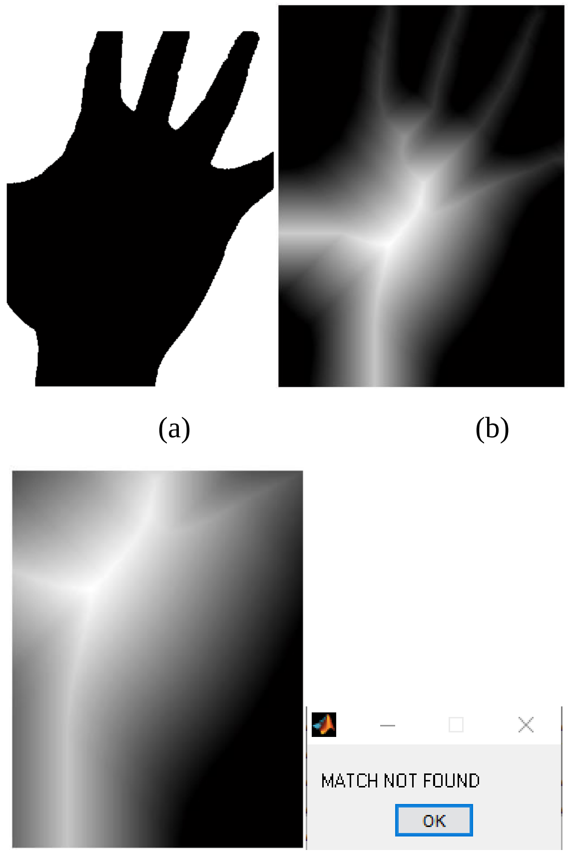


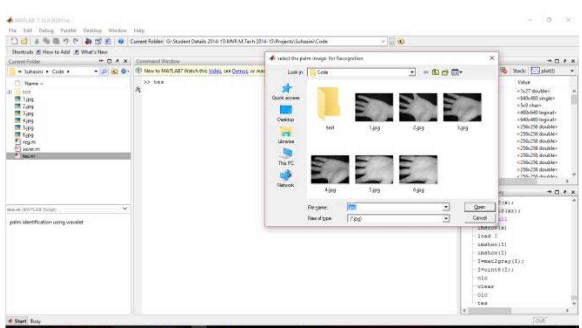
Fig. 12: Message box displayed after completion of test and matching process.



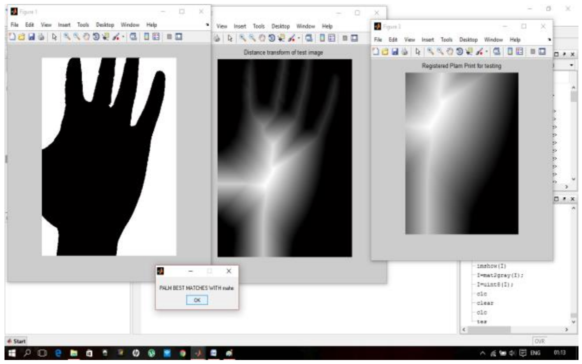
(a) (b)

(c) (d)

Fig. 13: Un saved file from data base (a) binary image (b) distance transform (c) registered palm print and (d) message box after testing with data base files



(a)



(b)

Fig. 14: screen shots of test image 4.jpg which has been saved with a specific file name in database.

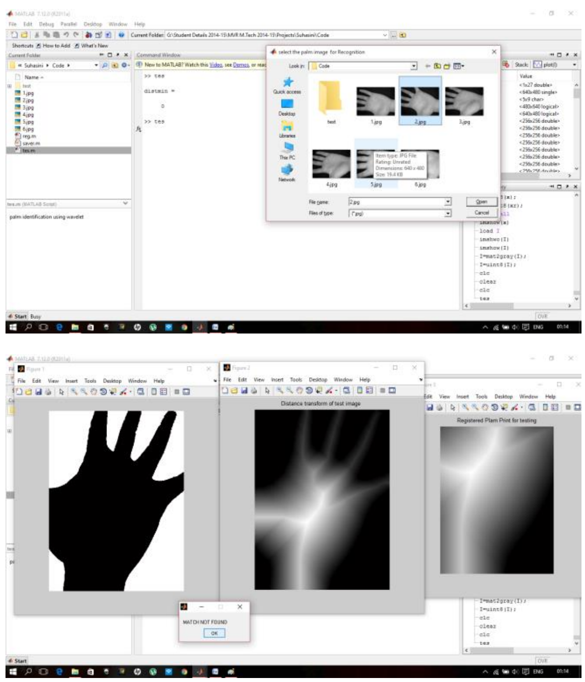


Fig. 15: Screen shots of test image 2.jpg which has not saved with a specific file name.

5. CONCLUSIONS

Here, we introduced a novel and highly secured biometric authentication model with palm print identification system using morphological ROI extraction with distance transform and un-decimated biorthogonal wavelet transform. Due to its multi scaling functionality, two different wavelet filter banks will be used to extract the features of distance transformed image to obtain the most effective feature factor for comparing with a test feature vector. The proposed model has proven that it has achieved 100% accuracy with several test images from the database.

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