# IMPLEMENTATION OF PALMPRINT RECOGNITION SYSTEM USING GLCM-PCA BASED DLCNN

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**Abstract**: Touchless palmprint recognition systems enable high-accuracy recognition of individuals through less-constrained and highly usable procedures that do not require the contact of the palm with a surface. To perform this recognition, methods based on local texture descriptors and Deep Learning Convolutional Neural Networks (DLCNNs) are currently used to extract highly discriminative features while compensating for variations in scale, rotation, and illumination in biometric samples. In particular, the main advantage of DLCNN-based methods is their ability to adapt to biometric samples captured with heterogeneous devices. However, the current methods rely on either supervised training algorithms, which require class labels (e.g., the identities of the individuals) during the training phase, or filters pretrained on general-purpose databases, which may not be specifically suitable for palmprint data. To achieve a high recognition accuracy with touchless palmprint samples captured using different devices while neither requiring class labels for training nor using pretrained filters, DLCNN that uses a newly developed method to tune palmprint specific filters through an unsupervised procedure based on grey level cooccurrence matrix (GLCM) responses and Principal Component Analysis (PCA), not requiring class labels during training. DLCNN is a new method of applying Gabor filters in a DLCNN and is designed to extract highly discriminative palmprint-specific descriptors and to adapt to heterogeneous databases. We will validate the innovative approach on several palmprint databases captured using different touchless acquisition procedures and heterogeneous devices, and in all cases, a recognition accuracy greater than that of the current methods in the literature was obtained.

**Keywords:** Principal Component Analysis,grey level cooccurrence matrix,Deep Learning Convolutional Neural Networks

## 1. INTRODUCTION

Biometrics based personal identification is getting wide acceptance in the networked society, replacing passwords and keys due to its 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 the 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.

## 2. RELATED WORK

In the literature, there are many researchers who have developed biometric authentication modules based on various spatial and transformation domain techniques. D. Huang, W. Jia, and D. Zhang [1] proposed a novel algorithm for the automatic classification of low-resolution palm prints. First the principal lines of the palm are defined using their position and thickness. Principal lines are defined and characterized by their position and thickness. A set of directional line detectors is devised for principal line extraction. By using these detectors, the potential line initials of the principal lines are extracted and then, based on the extracted potential line initials, the principal lines are extracted in their entirety using a recursive process. The local information about the extracted part of the principal line is used to decide a ROI and then a suitable line detector is chosen to extract the next part of the principal line in this ROI. After extracting the principal lines, some rules are presented for palm print classification.

A. Kong and D. Zhang [2] have presented a novel feature extraction method, the Competitive Coding Scheme for palm print identification. This scheme extracts the orientation information from the palm lines and stores it in the Competitive Code. An angular match with an effective implementation is developed for comparing Competitive Codes. Total execution time for verification is about 1s, which is fast enough for real-time applications. The proposed coding scheme has been evaluated using a database with 7,752 palm print images from 386 different palms. For verification, the proposed method can operate at a high genuine acceptance rate of 98.4% and a low false acceptance rate of 3*10-6.

Dai and Zhou [3] introduces high resolution approach for palm print recognition with multiple features extraction. Features like minutiae, density, orientation, and principal lines are taken for feature extraction. For orientation estimation the DFT and Radon-Transform-Based Orientation Estimation are used. For minutiae extraction Gabor filter is used for ridges enhancement according to the local ridge direction and density. Density map is calculated by using the composite algorithm, Gabor filter, Hough transform. And to extract the principal line features Hough transform is applied. SVM is used as the fusion method for the verification system and the proposed heuristic rule for the identification system.

Jiaa, Huanga and Zhang [4] and [5] have proposed palm print verification based on robust line orientation code. Modified finite Radon transform has been used for feature extraction, which extracts orientation feature. For matching of test image with a training image the line matching technique has been used which is based on pixel-to-area algorithm.

Zhang, Kong, You and Wong [6] have proposed Online Palm print Identification. The proposed system takes online palm prints, and uses low resolution images. Low pass filter and boundary tracking algorithm is used in preprocessing phase. Circular Gabor filter used for feature extraction and 2-D Gabor phase coding is used for feature representation. A normalized hamming distance is applied for matching.

J. You, W. Kong, D. Zhang, and K. Cheung [7] proposed a dynamic selection scheme by introducing global texture feature measurement and the detection of local interesting points. Our comparative study of palm print feature extraction shows that palm print patterns can be well described by textures, and the texture energy measurement possesses a large variance between different classes while retaining high compactness within the class. The coarse-level classification by global texture features is effective and essential to reduce the number of samples for further processing at fine level. The guided searching for the best matching based on interesting points improves the system efficiency further.

W. Li, J. You, and D. Zhang [8], have proposed an effective indexing and searching scheme for an image database to facilitate fast retrieval when the size of a palm print database is large. There are three key issues to be considered: feature extraction, indexing, and matching. In general, in an image database, the extracted features are often associated to the original images as indices. A search for the best matching is conducted in a layered fashion, where one feature is first selected to lead the search by reducing the set of candidates. Then other features are used to reduce the candidate set further. Such a process will be repeated until the final output is determined based on the given matching criteria. The selection of features plays an important role for efficient search. An effective feature selection scheme should exclude the most impossible candidates, compare easily, require small size of space for storage.

Prasad, Govindan and Sathidevi [9], have proposed Palm print Authentication Using Fusion of Wavelet Based Representations. Features extracted are Texture feature and line features. In proposed system pre-processing includes low pass filtering, segmentation, location of invariant points, and alignment and extraction of ROI. OWE used for feature extraction. The match scores are generated for texture and line features individually and in combined modes. Weighted sum rule and product rule is used for score level matching.

Cappelli, Ferrara, and Maio [9] proposed high resolution palm print recognition system which is based on minutiae extraction. Pre-processing is formed by segmentation of an image from its background. To enhance the quality of image, local frequencies and local orientations are estimated. Local orientation is estimated using fingerprint orientation extraction approach and local frequencies are estimated by counting the number of pixels between two consecutive peaks of gray level along the direction normal to local ridge orientation. Minutiae feature is extracted in feature extraction phase. To extract the minutiae features contextual filtering with Gabor filters approach is applied. Minutiae cylinder code has been used for matching the minutiae features.

A. Gyaourova and A. Ross [10] have proposed an indexing technique that can either employ the biometric matcher that is already present in the biometric system or use another independent matcher. Index codes are generated for each modality using the corresponding matcher. During retrieval, the index code of the probe is compared against those in the gallery using a similarity measure to retrieve a list of candidate identities for biometric matching. The proposed indexing technique on a chimeric multimodal database resulted in a reduction of the search space by an average of 84% at a 100% hit rate. The main factor for the amount of speedup during identification was the penetration rate of the indexing.

To overcome all the drawbacks of above works developed by many authors, here we supposed to introduce a highly secured biometric authentication system with palm print using UDBW transform and Morphological ROI extraction.

## 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

### *1.1. 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.

1.1.1. *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.

*1.1.2. 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.

*1.1.3. 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.

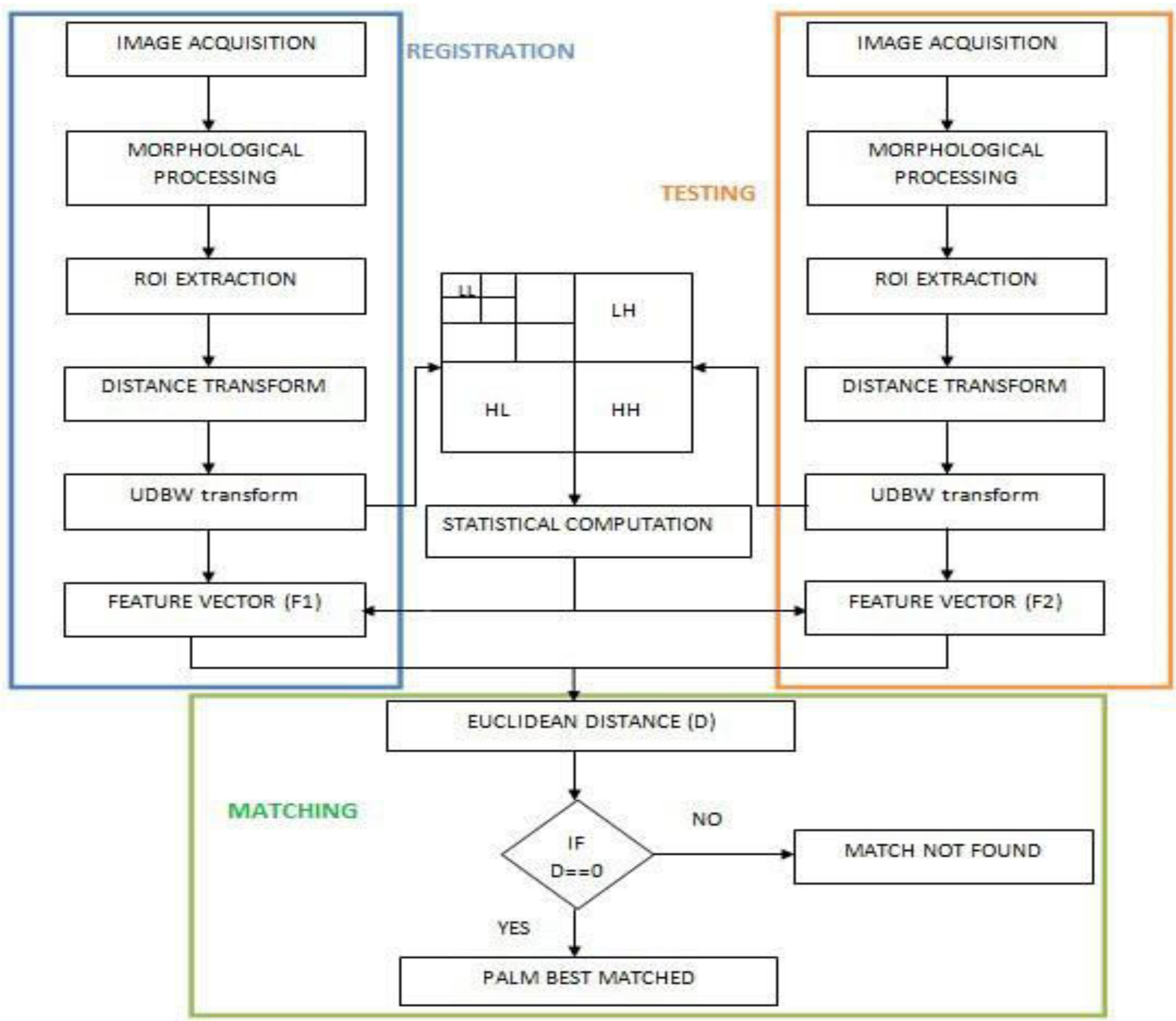



Fig.3.1 Flow chart of proposed palm print authentication system

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 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.3.2 Example of distance transform with chessboard metric

1.1.4. *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

$$V_{j+1} = V_j \oplus W_j \qquad (1)$$

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

$$\psi_{j,k} = 2^{\frac{j}{2}}\psi(2^j x - k) \qquad (2)$$

$$\tilde{\psi}_{j,k} = 2^{\frac{j}{2}}\tilde{\psi}(2^j x - k) \qquad (3)$$

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:

$$c_n^o = \sum_k h_{2n-k} c_k^1 \qquad (4)$$

$$d_n^o = \sum_k g_{2n-k} c_k^1 \qquad (5)$$

And the reconstruction is given by

$$c_l^1 = \sum_n \tilde{h}_{2n-l} c_n^o + \tilde{g}_{2n-l} d_n^o \qquad (6)$$

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

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

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

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:

$$\phi(x) = \sum_n \sqrt{2} \sum_n h_n \phi(2x - n) \qquad (7)$$

$$\tilde{\phi}(x) = \sqrt{2} \sum_n \tilde{h}_n \phi(2x - n) \qquad (8)$$

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

$$\psi(x) = \sqrt{2} \sum_n g_n \phi(2x - n) \qquad (9)$$

$$\tilde{\psi}(x) = \sqrt{2} \sum_n \tilde{g}_{-n+1} \phi(2x - n) \qquad (10)$$

***1.2. 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.

### *1.3. 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.

### 3.4. DLCNN

According to the facts, training and testing of DL-CNN involves in allowing every source image via a succession of convolution layers by a kernel or filter, rectified linear unit (ReLU), max pooling, fully connected layer and utilize SoftMax layer with classification layer to categorize the objects with probabilistic values ranging from $[0,1]$. Convolution layer as depicted in Figure 3.4 is the primary layer to extract the features from a source image and maintains the relationship between pixels by learning the features of image by employing tiny blocks of source data. It's a mathematical function which considers two inputs like source image $I(x,\ y,\ d)$ where $x$ and $y$ denotes the spatial coordinates i.e., number of rows and columns. $d$ is denoted as dimension of an image (here $d\ =\ 3$, since the source image is RGB) and a filter or kernel with similar size of input image and can be denoted as $F(k_x, k_y, d)$.

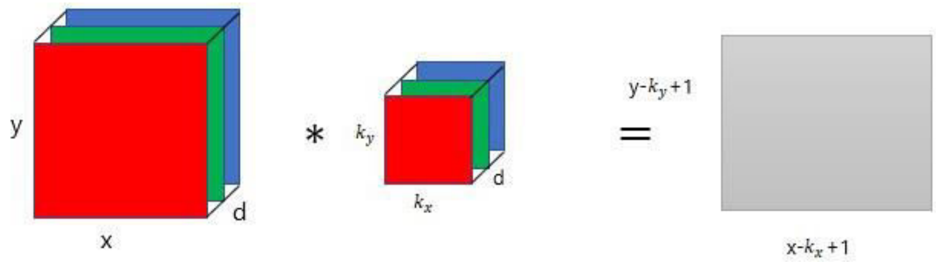
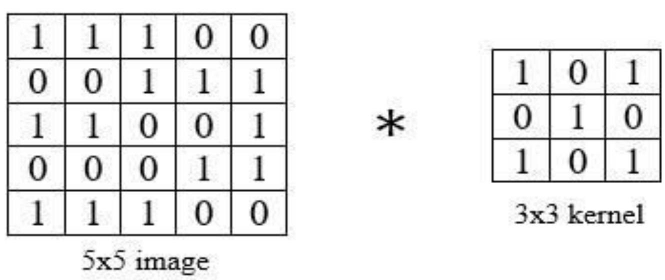
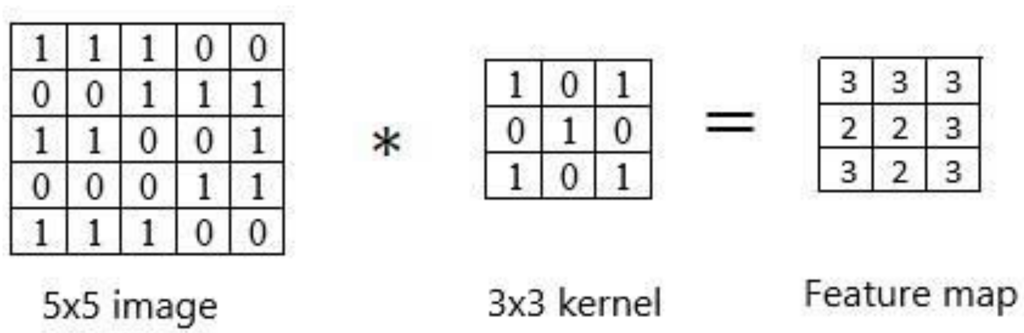



Fig. 3.3. Representation of convolution layer process

The output obtained from convolution process of input image and filter has a size of $C\,((x - k_x + 1), (\,y - k_y + 1), 1)$, which is referred as feature map. An example of convolution procedure is demonstrated in Figure 3.5. Let us assume an input image with a size of $5\ \times\ 5$ and the filter having the size of $3\ \times\ 3$. The feature map of input image is obtained by multiplying the input image values with the filter values as given in Figure 3.6.




(a)




(b)

Fig. 3.4. Example of convolution layer process (a) an image with size **5 × 5** is convolving with **3 × 3** kernel (b) Convolved feature map

**ReLU layer**: Networks those utilizes the rectifier operation for the hidden layers are cited as rectified linear unit (ReLU). This ReLU function $\mathcal{G}(\cdot)$ is a simple computation that returns the value given as input directly if the value of input is greater than zero else returns zero. This can be represented as mathematically using the function $max(\cdot)$ over the set of 0 and the input $x$ as follows:

$$\mathcal{G}(x) = \max\{0, x\}$$

**Max pooing layer**: This layer mitigates the number of parameters when there are larger size images. This can be called as subsampling or down sampling that mitigates the dimensionality of every feature map by preserving the important information. Max pooling considers the maximum element form the rectified feature map.

**3.5. Principal component analysis**

Principal component analysis is an approach of machine learning which is utilized to reduce the dimensionality. It utilizes simple operations of matrices from statistics and linear algebra to compute a projection of source data into the similar count or lesser dimensions. PCA can be thought of a projection approach where data with $m$-columns or features are projected into a subspace by $m$ or even lesser columns while preserving the most vital part of source data. Let $I$ be a source image matrix with a size of $n * m$ and results in $J$ which is a projection of $I$. The primary step is to compute the value of mean for every column. Next, the values in every column are centered by subtracting the value of mean column. Now, covariance of the centered matrix is computed. At last, compute the eigenvalue decomposition of every covariance matrix, which gives the list of eigenvalues or eigenvectors. These eigenvectors constitute the directions or components for the reduced subspace of $J$, whereas the peak amplitudes for the directions are represented by these eigenvectors. Now, these vectors can be sorted by the eigenvalues in descending order to render a ranking of elements or axes of the new subspace for $I$. Generally, $k$ eigenvectors will be selected which are referred principal components or features

**3.6. Euclidean distance**

To evaluate distances between query word image $I_q$ and retrieved word images $I_r$, a metric must be defined. We need a measurement method to tell how the query and retrieved word images are similar (bit per bit). Therefore, we want a similarity measure where the distance value will be the number of similar bits in the considered images.

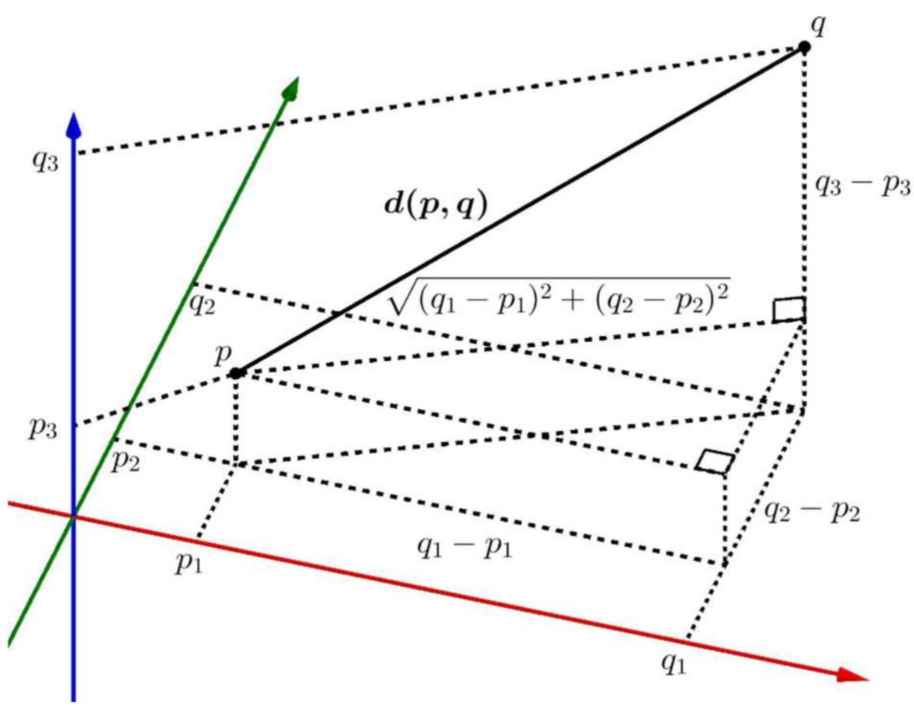
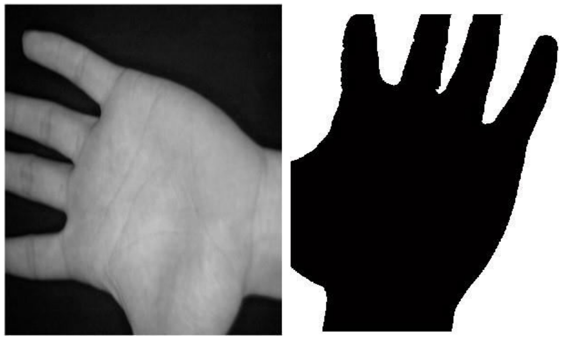


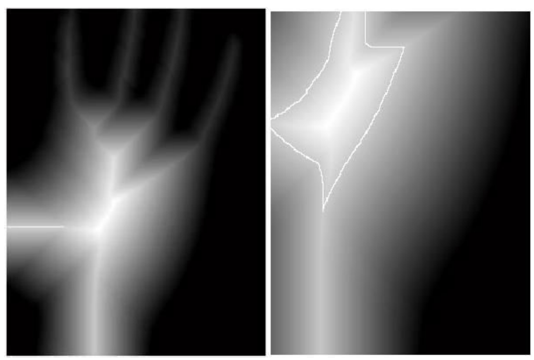

Fig. 3.5. Illustration of Euclidean distance

## 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. Fig1 shows that the original palm image for registration process described in section 3.1, 3 (a) shows the original palm image, 3(b) shows it's binary image with morphing, 3(c) shows that the distance transformed image of a binary image and finally 3 (d) is a registered palm print for authenticating a person for authorization into a particular task.



(a) (b)



(c) (d)

Fig1. (a) original palm image for registration (b) morphed image (c) distance transformed image and (d) registered palm image

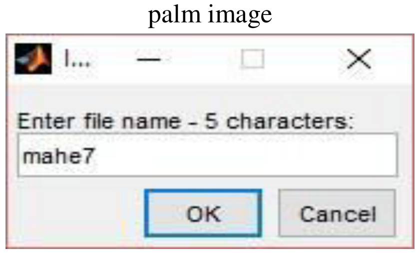



Fig2. Message box for saving the registered palm filename with mahe7

Fig3. distance transform of a test image

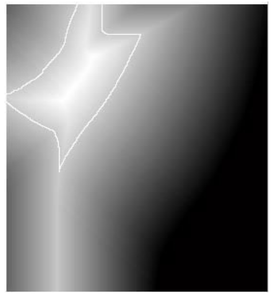
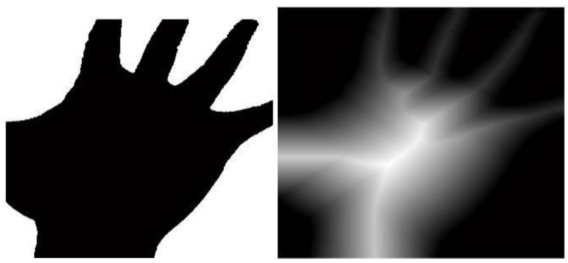
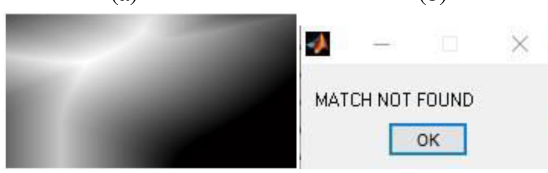


Fig4. Registered palm print of a test image


Fig5. Message box displayed after completion of test and matching process

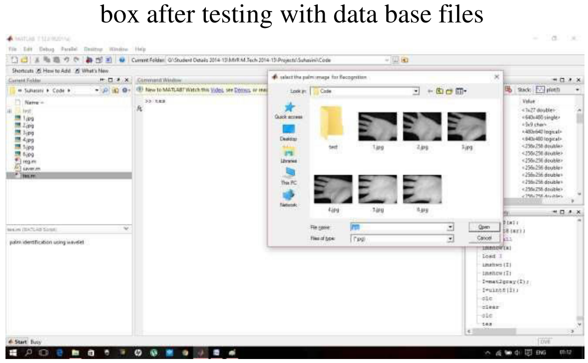


(a) (b)

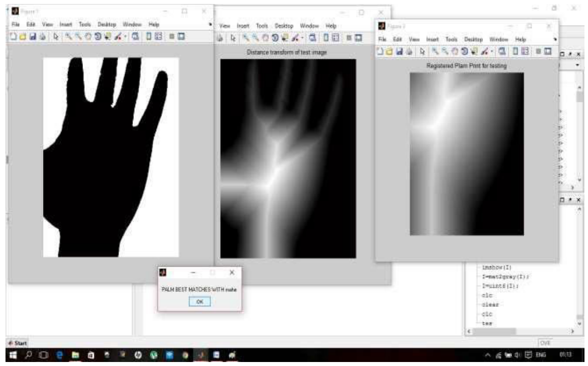



(c) (d)

Fig.6 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.7 screen shots of test image 4.jpg which has been saved with a specific file name in database

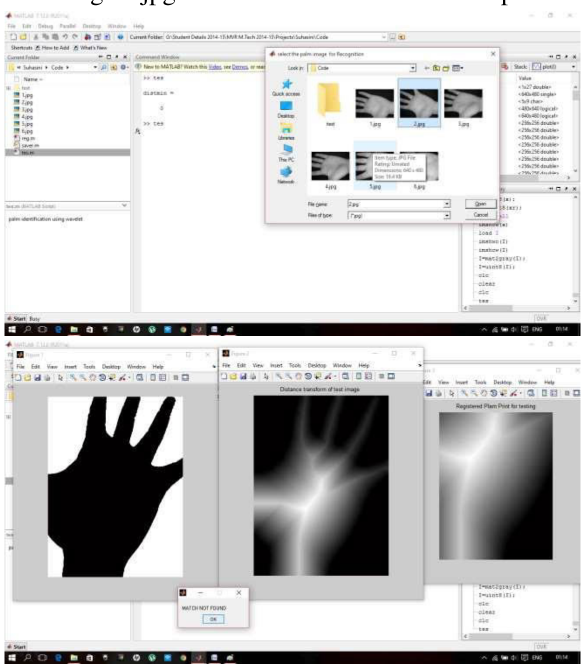


Fig.8 screen shots of test image 2.jpg which has not saved with a specific file name

## 5. CONCLUSIONS

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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