

Texture based Palm Print Recognition using Discrete Wavelet Transformation

Dhulipalla Nagajyothi
PG Student
Department of CSE
Chebrolu Engineering College, Guntur

K. Venkata Ramaiah
Associate Professor
Department of CSE
Chebrolu Engineering College, Guntur

ABSTRACT

Biometric based recognition is a method of verification that relies on the biological characteristics of each individual. They are processed based on their duplicate properties of being identical, portable, and difficult to reproduce. This paper represents a model for palm-print recognition system based on texture features using wavelet transformation. This is epitome for keeping personnel entry records in large enterprises. Using the simple approaches Discrete Wavelet Transformation (DWT) and Standard Deviation (σ), extraction of some texture characteristics from the ROI images of size 128X128. The images are then matched using Canberra Distance, Euclidean Distance and Manhattan distance. Among K images per user are used to create the training set, with K ranging from 1 to 4 and remaining images per user used for testing. In image recognition mode, the results are compared to the remaining images. The true acceptance rate is 98.86% obtained by using of Canberra distance.

Keywords

Biometrics, Palmprint Recognition, Texture Based Recognition, Canberra Distance, Euclidian Distance, Manhattan distance, Wavelet Transformation.

1. INTRODUCTION

Biometric based recognition is a way for automatically identifying people based on their behavioral or physiological features. Fingerprint, retina, iris, face, and palmprint are examples of physiological features. Palmprint-based person recognition is a novel biometric technique that is gaining popularity. Palmprint recognition is a type of biometric that uses unique features in human palms to recognize human identity. These features include major lines, wrinkles, ridges, minutiae, single points, and textures [1] Many feature extraction methods for palmprint recognition have already been proposed in the literature. While these methods have shown to be effective, the majority of them extract feature extraction on each pixel of a palmprint image while ignoring the image's region property [2] [3] . Because of their tiny feature size, fast matching speed, and high verification accuracy, palmprint recognition methods are popular [6] . As a result, new research on standard deviation-based Palmprint recognition focuses on how to improve the robustness of Palmprint images capture against fluctuations in orientation, location, and illumination by extracting Palmprint features.

A transform-based approach is commonly used to employ palm texture as a feature were Gabor filters[3] Fourier Transform[2] Cosine Transform[5] , and Wavelet[5] [6] are some of the papers that have been published. The

Gabor filter has strong feature extraction performance, but it takes a long time and is susceptible to non-linear distortions and rotations. The Fourier and Cosine Transformations are effective at extracting features from small amounts of data[7] . The usage will decrease as the feature vector is increased. A feature based on the Discrete Wavelet Transform (DWT) is proposed here. In comparison to traditional Fourier analysis, the wavelet transform has superior space-frequency localisation[8] Palmprint is rich in texture information; this texture pattern provides stable, unique, and difficult qualities for human recognition. The DWT has proven to be one of the most effective image processing transformations for data compression, feature extraction, and recognition.

Details of dataset utilized and feature extraction mechanism was presented in section 2, Experimental setting and results were present in section 3 and the conclusion and future enhancement work was posed in section 4.

2. FEATURE EXTRACTION USING DWT

A discrete wavelet transform varies significantly from other wavelet transforms in how it incorporates both frequency and location information about an images. The DWT of an image is determined by running the original image through a succession of low and high frequency filters. The detail coefficients are formed with a high pass filter, while the approximation coefficients are formed with low pass filters. The created half of the detail coefficients then stream towards the next level. Similarly, the mechanism will keep on going based on the degree of tiers.

A palmprint in a wavelet feature set other than the original image is described by feature extraction. A distinguishing trait should have a big variance across individuals and a modest variance between samples from the same person. In comparison to traditional Fourier analysis, the wavelet transform has superior space-frequency localization. As a result, it's well-suited to evaluate image in which the majority of the information content is represented by spatially localized components like edges and borders. The original image is split into four sub-bands at the first level, yielding a scaling component with global low-pass information and three wavelet components for horizontal, vertical, and diagonal features[10] .

Here Hong-Kong polytechnic University's' palmprint dataset version 1 have been used. The PoU palmprint database[11] , with 400 users divided into two parts, each with ten samples, for a total of 8000 grayscale images. Palm images are 128X128 pixels in size. Sample palmprint image shown in Figure 1



Figure 1. Sample palmprint Region of Interest

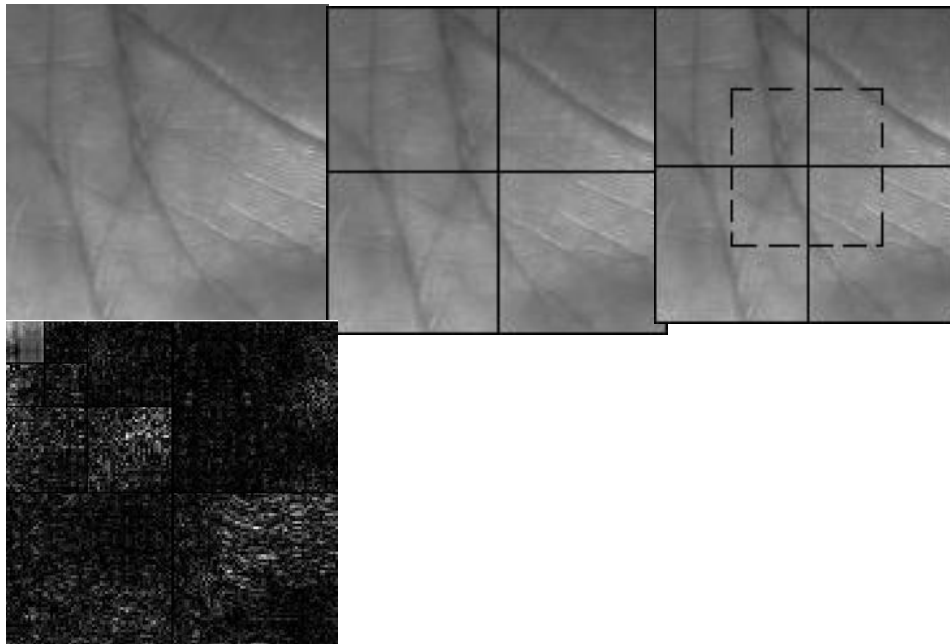
The following is the processor for obtaining the Feature Vector:

- Step 1:** Read the ROI image [Figure 2a].
- Step 2:** Make the Sub-images into 64X64 which are non-overlapped [Figure 2b].
- Step 3:** Make the Sub-image of 64X64 from intersect of above sub-images [Figure 2c].
- Step 4:** Now apply Wavelet Transformation up to 3 levels. And then consider the Horizontal, Vertical and

Diagonal details [Figure 2d] of image and calculate the Standard deviation for each detail.

- Step 5:** Make the sub-images of 32X32 which are non-overlapped [Figure 2e].
- Step 6:** Make the Sub-images of 32X32 from intersect of above sub-images [Figure 2f].
- Step 7:** Now apply Wavelet Transformation upto single level. And then consider the Horizontal, Vertical and Diagonal details [Figure 2g] of images and calculate the Standard deviation for each detail.
- Step 8:** Make the sub-images of 16X16 which are non-overlapped [Figure 2h].
- Step 9:** Make the sub-images of 16X16 from intersect of above sub-images [Figure 2i].
- Step 10:** Calculate Standard deviation for sub-images.

The wavelet transformation details are considered in an order [Figure 2j], horizontal, vertical and diagonal are taken from inner level to outer level, i.e. Consider from lower level 3 to higher level 1.



[a]

[b]

[c]

[d]

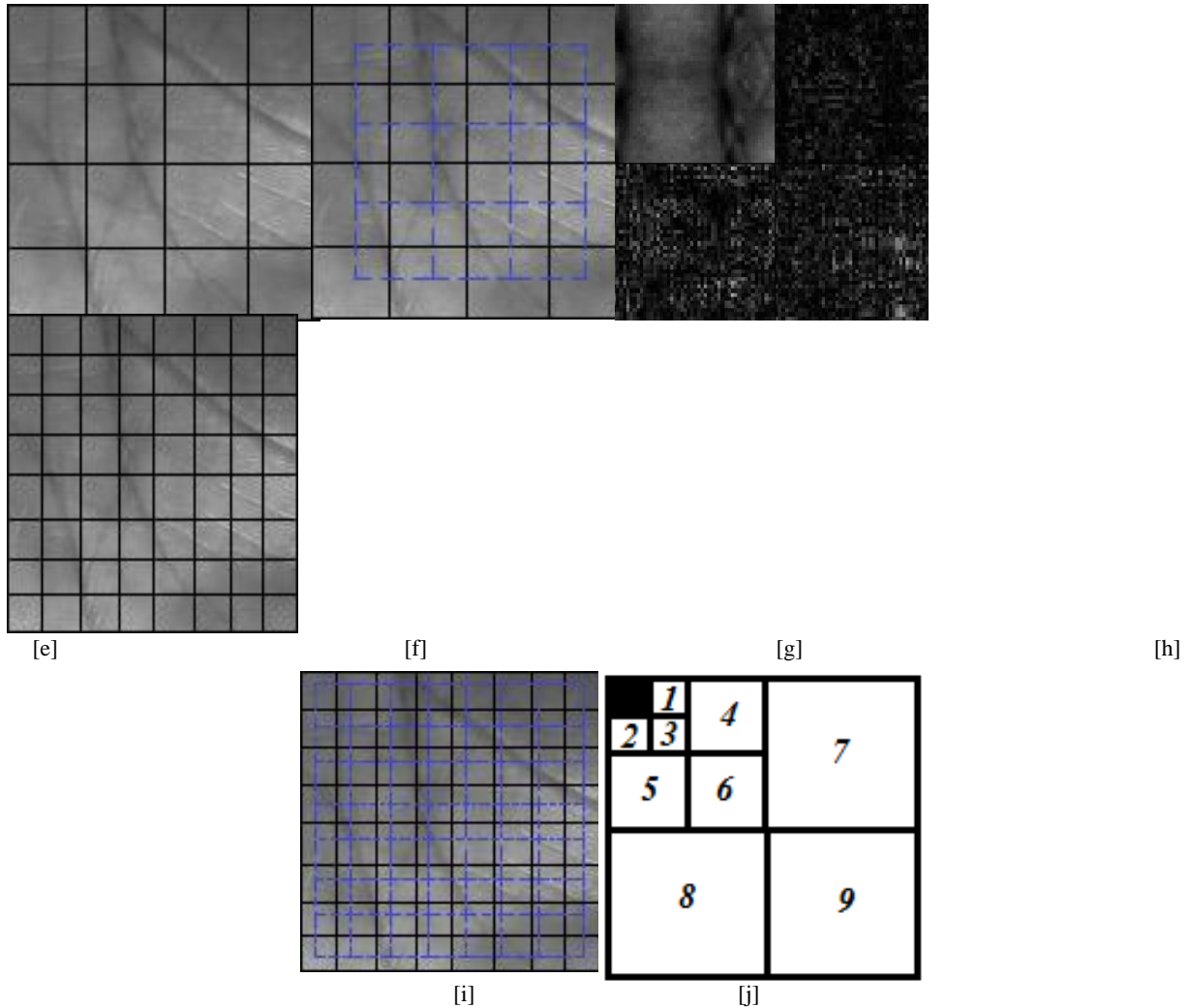


Figure 2. Feature Extraction Processor

[a] Original ROI. [b] Non-overlapped 64 X 64 Sub-images. [c] Intersected 64X64 Sub-image.
[d] 3 Level wave Transformation. [e] Non-overlapped 32X32 Sub-images. [f] Intersected 32X32 Sub-images.
[g] 1 Level wave Transformation. [h] Non-overlapping 16 X 16 Sub-images. [i] Intersected 16 X 16 Sub-images.
[j] The order of details read from 3 level wave transformation

In 32X32 as the size has limited number of pixels it can be applicable up-to only one level. So, that it directly took them as order.

3. EXPERIMENTAL SETTING AND RESULTS

For each sub-image, DWT decomposition is performed up to three levels for 64X64, one level for 32X32, and no level for 16X16. The standard deviation for each detail is then determined by using of the following equation.

$$\sigma = \sqrt{\frac{1}{n} \sum_{i=1}^n (G_i^2 - \mu^2)}$$

Where n is no. of pixels in image, i is position of the pixel varies from 1 to n, G represents the sub-image and μ represents the mean value of the sub image. Mean calculated by using of following equation.

$$\mu = \frac{(\sum_{i=1}^n G_i^2)}{n}$$

For each approach, a total feature vector of 233 (64X64 yields (4+1=5)x9=45, 32X32 offers (16+9)x3=75, and 16X16 gives (64+49)x1=113) is calculated.

K Palmprint Grayscale images were used to generate the database, with K ranging from 1 to 4. The rate of recognition is increased when more than one image is utilised to train. In recognition mode, the algorithm is tested by comparing the remaining images in the database. The following TABLE 1 shows the total number of images utilised for training and testing.

TABLE 1. Total number of images used for training and testing

No. of Images used	Training Set	Testing Set
1	1x2x400=800	9x2x400=7200
2	2x2x400=1600	8x2x400=6400
3	3x2x400=2400	7x2x400=5600
4	4x2x400=3200	6x2x400=4800

The feature vector is now ready to be tested after the standard deviation has been determined. By comparing the

database features vector of the database picture and the test image, the testing image is calculated.

The matching process will proceed using a distance methods of Canberra, Euclidean and Manhattan. The following formula will be used to calculate the distance between two vectors using Canberra distance method: [10]

$$D = \sum_i \frac{|A_i - B_i|}{A_i + B_i}$$

The following formula will be used to calculate the distance between two vectors using Euclidean distance method [10]

$$D = \sqrt{\sum_i (A_i - B_i)^2}$$

The following formula will be used to calculate the distance between two vectors using Manhattan distance method [10]

$$D = \sum_i |A_i - B_i|$$

Where **A** and **B** are two feature vectors, one from training dataset and the other is obtained from testing image, *i* is the element's position and *D* is distance measured. In the way distances are computed with each entry in the database. And finally which ever has minimum distance is considered as recognised one for test image.

TABLE 2 will display the results. The percentage Genuine Acceptance rate for comparing all of the test images to the feature vector that has previously been constructed.

TABLE 2. Genuine Acceptance Rate

No. of samples Used	1	2	3	4
Using Euclidean distance	90.67	94.66	96.96	97.37
Using Canberra distance	91.986	96.45	98.053	98.86
Using Manhattan distance	89.5	93.5	97.84	96.96

Using Standard deviation as simple feature vector it has given %GAR up to 98.86%.

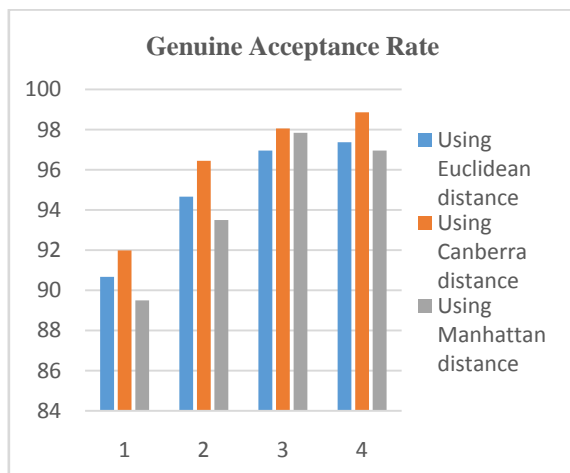


Figure 3. Genuine acceptance rate for test images

4. CONCLUSION

For feature extraction, the texture pattern dispersed across palmprint images is used. These characteristics were retrieved from DWT and shown to be beneficial in improving performance. The performance improves when the feature vector is produced using a larger number of training images, according to the findings of the experiments. The method effectively makes use of DWT's strategic merits using Canberra distance method over Euclidean distance and Manhattan distance methods with genuine acceptance rate of 98.86%.

Future work is related to time consumption for feature extraction. This model has improved some recognition mechanism but still this model consuming a lot of time to extract the palmprint features. It took approximately 1300 milliseconds to 3200 milliseconds per image. For set of data images it suites well but coming to large data sets it might not be suitable. So In future work is planned for reduction of time consumption for overall mechanism.

5. REFERENCES

- [1] Aravind Nalamothu, et.al "Texture based Palmprint Recognition using Simple Methods". International Journal of Computer Applications, July 2012. 10.5120/7761-0827
- [2] W. Li, et.al "Palmprint Identification by Fourier Transform", International Journal of Pattern Recognition and Artificial Intelligence, 417-432-2002
- [3] J. Lu, et.al "Enhanced Gabor-based region covariance matrices for Palmprint Recognition", International journal of Electronics Letters, Aug 2009.
- [4] Wang Xuan, et.al "Palmprint Verification based on 2D- Gabor Wavelet and Pulse coupled neural network", Knowl. Based Syst(2011),doi:10.1016/j.knosys.
- [5] Manisha, et.al "Texture Based Palmprint Identification Using DCT Features", Intern. Conf. on Advances in Pattern Recognition, 978-0-7695-3520-3/09.
- [6] Pritee, et. al "Analysis of palmprint Verification using Wavelet filter and competitive code", Intern. Confe. on compu. Intelli. and commu. Systems. 978-0-7695-4254-6/10
- [7] O. Nibouuche, et. al "Analysis of performance of palmprint matching with enforced sparsity", Digital Signal Processing(2011)
- [8] Hafiz Intiaz, et. al "A Spectral Domain Dominant Feature Extraction Algorithm for Palmprint Recognition", International Journal of Image processing(IJIP), Volume-5,2011
- [9] A. Kong, et. al " A survey of palmprint recognition", pattern recognition, vol.42,2009
- [10] "Digital Image Processing", 3rd Edition, by Rafael C. Gonzalez, Richard E. Woods
- [11] PolyU Palmprint Database, <http://www.comp.polyu.edu.hk/~biometrics/>.