ANANALYSIS ON BIOMETRIC AUTHENTIFICATION USING FINGER PRINT RECOGNITION SYSTEM

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Abstract:- ***Fingerprint recognition is a complex pattern recognition problem. The real challenge is matching fingerprints is the high variability commonly found between different impressions of the same finger which is caused by factors like rotation between different acquisitions, skin conditions like dirt, cut etc. or noise of the sensor and so on. The vast majority of contemporary fingerprint authentication systems are feature extraction based i.e., minutiae based. The Euclidean Distance achieved is different for different images and for matched images, its value it either equal or less than the set threshold value i.e., 1. The accuracy of matched images for different images at different angle is high. Lower the Euclidean Distance and less number of matched images, the more accurate is the system. Polar Harmonic Transforms are very fast and efficient, providing high performance based on the number of fingerprints present in the database.***

Keywords:- Minutiae, Polar harmonic transforms, Polar complex exponential Transform, Polar cosine transform, False acceptance rate, False rejection rate.

1. INTRODUCTION

Face recognition is a challenge in image analysis and computer vision and received a great attention in last few years. Here we have mentioned some of the face recognition techniques that are worth useful and there are many like these techniques. Basic format of face recognition is we already have a data base for registered faces and an algorithm that is designed to verify the input image with the data base and confirm the identities. Face recognition have become more useful for the security reasons also because in previous everyone uses the pin, passwords, etc. for identification but face recognition, vein recognition, iris, voice recognition and retina recognition have become the more secured ways to deal with the security. Here we have proposed many face detection techniques and based on that we found best ways to get the best results

Diverse parts of human physiology zone unit won't to validate a man's personality. The exploration of determining the personality with reference to very surprising qualities characteristic of human being is termed bioscience. The qualities trait may be by and large grouped into 2 classes i.e. physiological and behavioural. Estimation of physical
choices for private distinguishing proof is partner age late take after that goes back to the Egyptians period. Be that as it may, it was not till nineteenth century that the investigation of bioscience was widely utilized for private recognizable proof and security associated issues. With the headway in innovation, recognizable proof has been wide utilized for access administration, implementation, and security framework. somebody may be known on diverse physiological and behavioural attributes like fingerprints, confronts, iris, hand immaculate science, walk, ear example, voice acknowledgment, keystroke example and warm mark.

This paper proposes on colour based, motion based, blink detection and feature detection techniques that will all help. We have made a holistic, featured based and hybrid approach in face detection techniques.

2. PROBLEM FORMULATION

All the previous work has some drawback of efficiency of image selection and detection therefore it is being improved through our proposed method of histogram based FD

2.1 OBJECTIVE

The main objective of thesis to proposed different method of face detection based on histogram .we will compare its results with previous on face detection.

3. RESULT AND DISCUSSION

One image from the database is taken as a training image. Again, for this big image, the crop in the circle is reduced to reduce the number of pixels. The circle is usually made to remove its edge, so that we can move the image during training sessions and at any angle during the testing session. Upon implementing the PHP algorithm, it removes the attributes of the image. After this, a test image is taken from the database. The image rotates at the desired angle and the PHP algorithm applies. Now, the Euclidean distance is calculated between training and test images. Then, the system shows whether the fingerprint has been matched or not. False acceptance rate (FAR) and false rejection rate (FRR) are also calculated. Reduce FAR and FRR values, the results are more accurate.

The proposed approach has been evaluated and tested on the CASIA database. This database contains 100 different fingerprint images. From an image database, each test image is rotated from different angles and to match the false rejection rate, it is matched with the original image, so false rejection rate divided by the number of false rejection rate (FRR) identification attempts. The ratio of numbers is. FRR is also known as a false non-match rate or type I error. FRR is a piece of real fingerprint that is rejected.

Again, from one image database, each test image is rotated from different angles and the match is matched to the original image to calculate the false acceptance rate. Therefore, there is a proportion of the number of false approvals divided by the number of false acceptance rates (FARs)identification attempts. FAR is also known as NonMatch Rate or Type II error.

The FAR is the fraction of imposter fingerprints which are accepted.

FAR and FRR are very much dependent on the biometric factor that is used and on the technical implementation of the biometric solution. Furthermore, the FRR is strongly person dependent, a personal FRR can be determined for each individual. Also, FRR might increase due to environmental conditions or incorrect use, for example when using dirty fingers on a finger print reader. Mostly the FRR lowers when a user gains more experience in how to use the biometric device or software. FAR and FRR are key metrics for biometric solutions for, some biometric devices or software even allow to tune them so that the system more quickly matches or rejects.

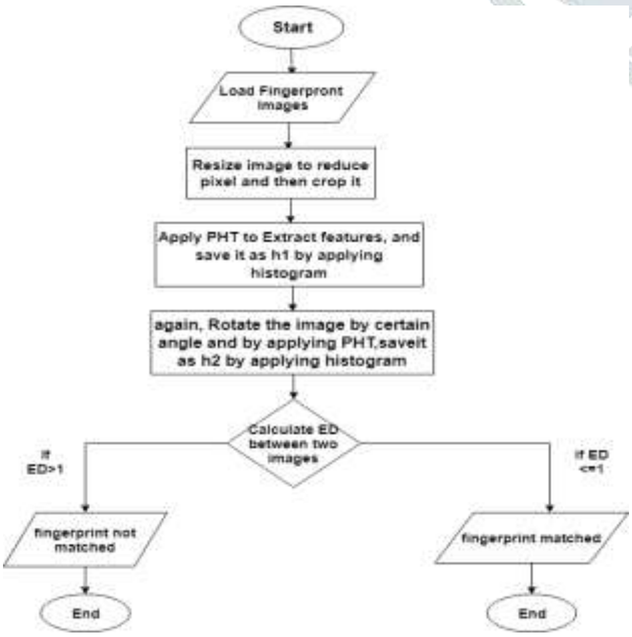
From the database images, only one image is considered the training image with testing images being hundred. The training image is matched with the hundred testing images

For a training image number 11, with the angle of rotation 100, the number of matched images is 13 and non-matched images are

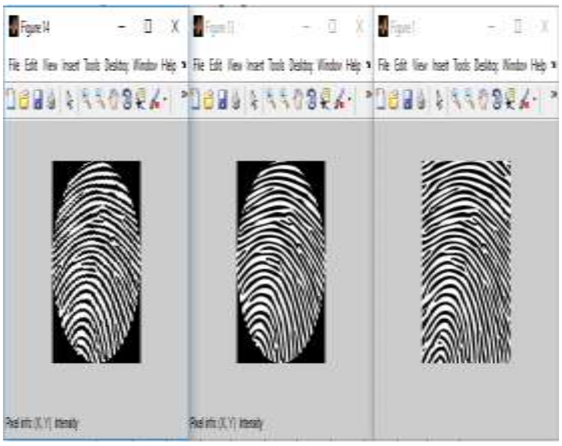
3.1 Algorithm

Polar Harmonic Transform.

1. Load a fingerprint image.
2. Resize the image to reduce pixels(for large images), 150∗150 pixels
3. Crop the image to get region of interest (ROI)
4. Apply PHT on the fingerprint image
5. Extract features of the cropped image
6. Apply histogram, h1 and save the image(A)
7. Take a cropped image from step(2)
8. Rotate the image at specific angles
9. Again apply PHT on the cropped image
10. Apply histogram, h2 and save the new image(B)
11. Calculate Euclidean Distance(ED) between the two images i.e., image(A) and image(B) as:
$$ED(h1, h2) = \sqrt{mean(h1 - h2)^2}$$
12. Loop through step 8 to 11 to calculate ED at various rotated angles
13. Fingerprint Matching: If ED≤1 i.e., set threshold value, then, the result is matched else, not matched.
14. Repeat steps 1–13 using PHT



Note -Lower the value of Euclidean Distance, more accurately matched the image.



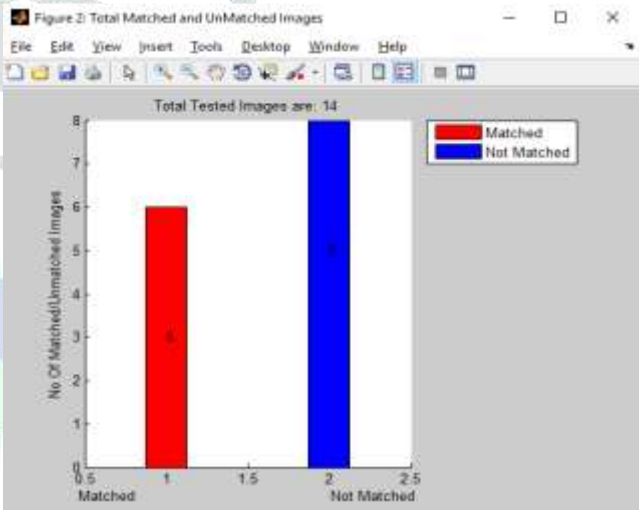
4. RESULT ANALYSIS

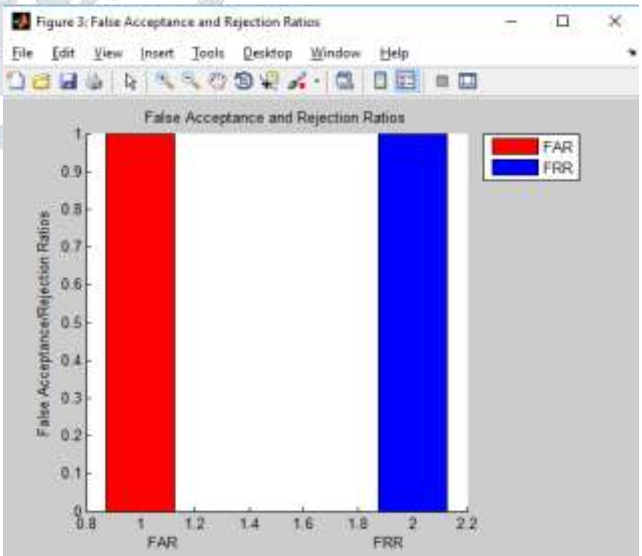
Enter Angles to Rotate the Image: 10

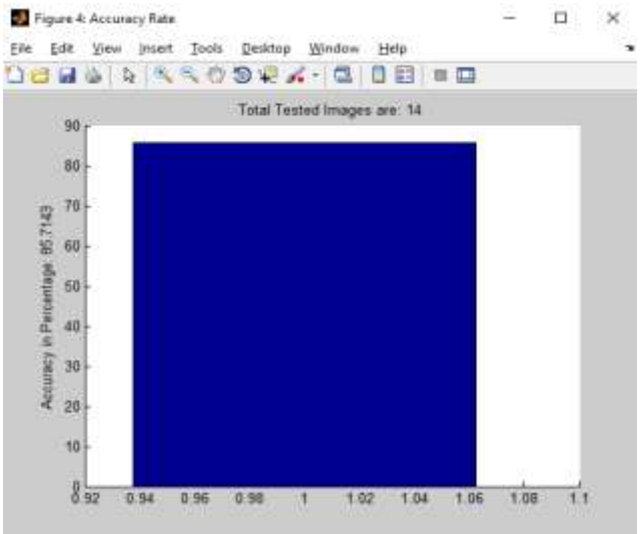
Image No 1 Image not matched at angle 10 with EuclDist49.4975

Image No 13Image matched at angle 10 with EuclDist0.53033

Image No 14 Image not matched at angle 10 with EuclDist214.7837







5. RESULT DISCUSSION

The Euclidean Distance achieved is different for different images and for matched images, its value it either equal or less than the set threshold value i.e., 1.The accuracy of matched images for different images at different angle is high.

Lower the Euclidean Distance and less number of matched images, the more accurate is the system.

Image No 13

- Image matched at angle 10 with**EuclDist0.53033**

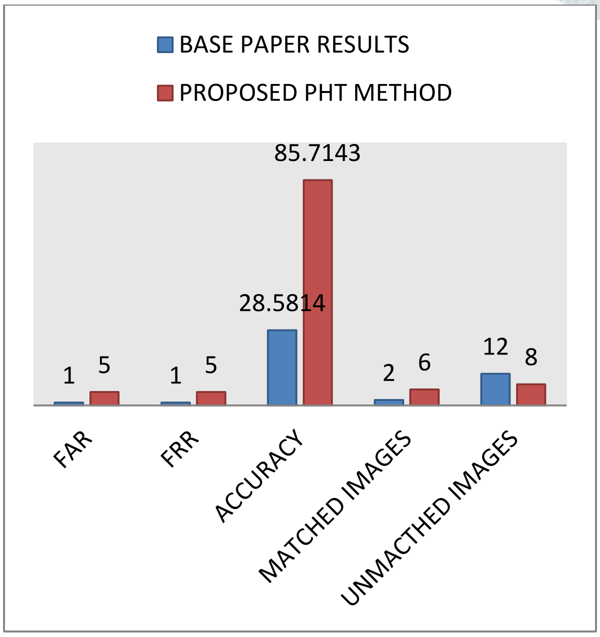
Image No 14

- Image not matched at angle 10 with**EuclDist214.7837**

6. COMPARISON

The analysis of comparison between the two results obtained is tabulated below:

Parameter	Base Paper Result	PROPOSED PHT
Match ED	0.53033	0.60008-0.24856i
Un-matched ED	214.7837	27.8143-11.5211i
Average Match Score	28.5814%	85.7143%
Total images 14	Matched 2	Matched 6
Performance	Average	Excellent



7. CONCLUSION

A new fingerprint recognition system has been proposed in this thesis. A set of Polar Harmonic Transforms (PHTs) such as Polar Cosine Exponential Transform, Polar Cosine Transform and Polar Sine Transform, proposed to generate rotation invariant features for fingerprint identification. The kernel function consists of sinusoidal function that is inherently computation intensive which is used to generate rotation invariant features. The result shows both matched and unmatched images of the database system irrespective of the angle of rotation both with low values of FAR and FRR which shows that the probability of errors is the least. A large set of database images are tested with training images and at various angles of rotation and the images are matched based on the Euclidean distance. The Euclidean Distance achieved is different for different images and for matched images, its value it either equal or less than the set threshold value i.e., 1. The accuracy of matched images for different images at different angle is high. Lower the Euclidean Distance and less number of matched images, the more accurate is the system. Polar Harmonic Transforms are very fast and efficient, providing high performance based on the number of fingerprints present in the database.

6.1 Future Work

In future, the proposed algorithm can be applied on different databases and colored histogram based approaches can also be suggested

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