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Palm Recognition Using OpenCV on BeagleBoard Xm: DM3730

[1] Khushi Diccar
[1] Professor, Electronics and Tele Communication
Deogiri Institute of Engineering & Management Studies, Aurangabad, India

Abstract: -- **The palm print is a new and emerging biometric feature for personal recognition. The system provides the basic idea about palm print recognition using OpenCV libraries, principal component analysis (PCA) algorithm and Beagleboard XM: DM3730 platform, OpenCV library is having rich functionality for image processing. The results of the experiments show the efficiency of the palm recognition system is 78% for 0.00 matching confidence threshold.**

Keywords— Biometric; PCA; Harr Cascade classifier

I. INTRODUCTION

Biometric recognition refers to the recognition of an individual based on certain distinguishable physical or behavioral characteristic which are unique to that individual. Personal identification number or identity cards are used in many applications [1], however these types of identity recognition methods have serious disadvantages, as they become less secure in a world of theft and terrorism. On the other hand biometric identification has gained importance due to high degree of security which is essential by todays modern organization like banking, airport and railway security, attendance control, access to restricted areas etc. Hence biometric identification systems which ensures reliability and is highly resistant to the mentioned risks should be implemented. There are two categories based on the traits used for identification:

A. Behavioral Biometrics:

These traits depend on the behavior and mood of the person and they are not constant throughout life. The common behavioral traits are signature, speaking style, keystroke, gait, voice, hand gesture etc.

B. Physiological Biometrics:

These traits depend on the physical body parts of a person which are unique and remain constant throughout life. The common physiological biometric traits are fingerprint, DNA, face, palm print, iris, retina etc [2].

Palm print being most reliable, recognizes a person on the basis of the palm print of that person. The palm patterns for each person are always unique [3] with the permanent ridge structure which is formed at about the thirteenth week of the embryonic development, which gets completed by the eighteenth week therefore even the monozygotic twins have unique palm prints [4]. As the palm print is distinctive, easily captured by devices as well as contains additional features like fixed line structure, low intrusiveness and requires low cost capturing device, low resolution imaging, it is mostly preferred compared with the other biometric traits.

II. LITERATURE REVIEW

David Zhang and et al. [1] used palmprint technology with low resolution images and achieved the effective way to personal identification, in which 2D gabor phase encoding scheme is used. Lin Hong and et al. [5] have also worked on fingerprint image enhancement and evaluated the performance using the goodness index of the extracted minutiae and the accuracy of an online fingerprint verification system, and come up with improved goodness index and verification accuracy. Aleix and Avinash [6] worked on face database and compared LDA and PCA for object recognition and concluded that when training dataset is small PCA performs well as compared to LDA as PCA is less sensitive to different training datasets. Chin-Chuan Han and et al. [7] also worked on palmprint for personal authentication, wherein the Sobel morphological operation to extract the features of ROI is used. Template matching and back propagation neural networks are used to measure the similarity between the two palmprint images. To avoid the transformation of image prior to feature extraction, Jian Yang and et al. [8] proposed 2DPCA and implemented the system for face recognition which proved that 2DPCA is more efficient than PCA. Guang Ming Lu and et al. [9] also used palm print as the biometric trait; wherein Independent Component Analysis (ICA) method for person's

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identification is used, which minimizes the statistical independence of the components. Slobodan and Ivan [10] used eigenpalm along with eigenfinger features to extract human hand features which is based on K-L transform with almost 100% reliability.Pablo H and et al. [11] used correlation filter classifiers trained in ROI specific for each palm for palm print recognition using the palm line algorithm. Anil K. Jain and Jianjiang Feng [12] worked on a palm print identification system for forensic applications using minutiae as features, fixed-length minutia descriptor and MinutiaCode, which used a high resolution camera to capture the images. David Zhang and et al. [13, 14, 15] explores a new approach of 3-D palmprint recognition approach by exploiting the 3-D structural information of the palm surface, which has reliable and high recognition performance. From the above all literature review, it is found that the systems which are using palm vein, ECG, gait, retina etc. require high performance image capturing devices, large memory, large processing time etc, while other systems where palm print has used to recognition, 3 D recognition overcome the issues with 2 D recognition, however has added the overhead of costly image capturing equipments and reduces the speed of operation. Palmprint with 2 D PCA using opencv on beagle board platform is the new and emerging technology to be used.

III. SYSTEM OVERVIEW

The system Includes beagleboard xm platform and opencv libraries for palm print recognition. Fig.1 gives overall idea about the system.

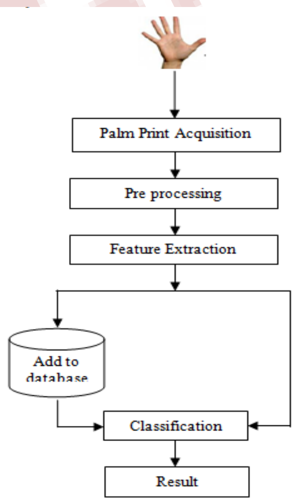

Fig. 1. SYSTEM BLOCK DIAGRAM

- Palm Print Acquisition - This system uses any usb camera (up to 3 MP) for the capturing real time input. An acquisition module can request a palm image from several different environments.
- Pre Processing - In this module palm images are normalized and enhanced to improve the recognition performance of the system. Haar Cascade classifier palm detector analyses each image location and classifies it as "Palm" or "Not palm". The classifier uses data stored in an XML file to decide how to classify each image location.
- Feature Extraction - After pre-processing on palm image, eigenpalms (PCA) for palm Recognition is done. Eigenpalm consists of two phases: learning and recognition. In the learning phase, the system finds eigenpalm of the image. In the recognition phase, it responds to the closest image from feature database to the new palm image. The result of the system is displayed on the monitor with DVI- D port.
- Hardware used - BeagleBoard XM DM3730 with angstrom OS and opencv library is used as platform to execute the system provides cost effective, easy to handle and stand alone platform.

The system is easy to handle, very cost effective as it does not require high resolution cameras, thus can be used for security, law enforcement, legislature, residential security, e-commerce etc. The database generation is easy, harmless and secured as compared to other biometric systems.

IV. RESULTS

The system works for all type of palm prints in all types of environment. Performance of the system is measured in certain standard terms. These are False Acceptance Rate (FAR), False Rejection Rate (FRR), Equal Error Rate (EER). Following table I gives FAR against matching confidence threshold (MCT) for thesystem. By analyzing threshold values it can be concluded that FAR goes on increasing as threshold values moves from positive to negative values. Hence threshold value is set to a value at which acceptable error occurs.

TABLE I. FALSE ACCEPTANCE RATE VS. MATCING CONFIDANCE THRESHOLD

Sr. No.	MCT	Number of forged palms accepted (out of 50)	FAR (%)
1	3.00	2	4

Sr. No.	MCT	Number of forged palms accepted (out of 50)	FAR (%)
2	2.00	3	6
3	1.00	6	12
4	0.00	11	22
5	-1.00	23	46
6	-2.00	25	50
7	-3.00	37	74

Following Fig. 2 gives FAR against MCT for the system.

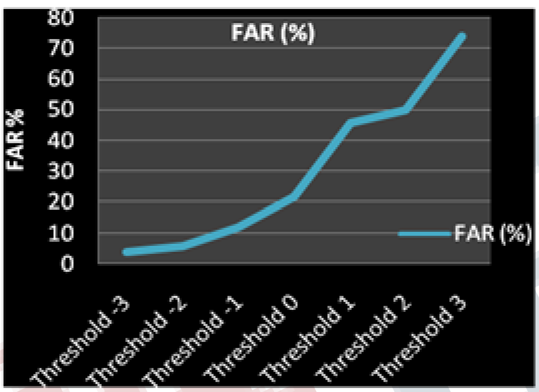

Fig. 2. GRAPH OF FALSE ACCEPTANCE RATE VS. MATCING CONFIDANCE THRESHOLD

Following table II gives FRR against MCT for the system.

TABLE II. FALSE REJECTION RATE VS. MATCHING CONFIDANCE THRESHOLD

Sr. No.	MCT	Number of genuine palms rejected (out of 50)	FRR (%)
1	3.00	36	72
2	2.00	27	54
3	1.00	26	52
4	0.00	11	22
5	-1.00	5	10
6	-2.00	4	8
7	-3.00	1	2

Following Fig. 3 gives FRR against MCT for the system.

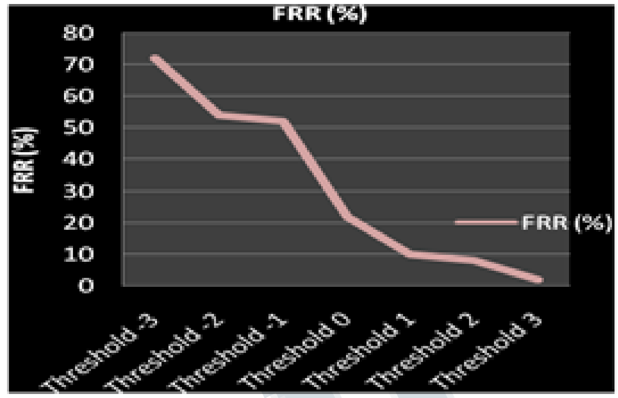

Fig. 3. GRAPH OF FALSE REJECTION RATE VS. MATCING CONFIDANCE THRESHOLD

Palm print recognition system should have and acceptable tradeoff between a low FAR and low FRR. Equal error rate (EER) is a intersection at which FAR and FRR is same. Following Fig. 4 shows the EER occurs at matching confidence threshold=0.00 at which FAR=FRR=22 %. Following graph gives EER against matching confidence threshold for the system.

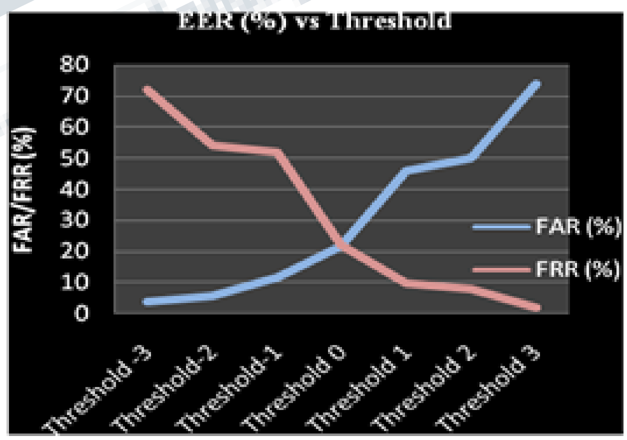

Fig. 4. GRAPH OF EQUAL ERROR RATE VS. MATCING CONFIDANCE THRESHOLD

Accuracy is calculated for 250 images for 50 persons against various matching confidence threshold values as shown in following table III.

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TABLE III. ACCURACY VS. MATCHING CONFIDANCE THRESHOLD

Sr. No.	MCT	Number of genuine palms rejected (out of 50)	Accuracy (%)
1	3.00	2	96
2	2.00	3	94
3	1.00	6	88
4	0.00	11	78
5	-1.00	23	54
6	-2.00	25	50
7	-3.00	37	26

Following Fig. 5 gives accuracy against MCT for the system.

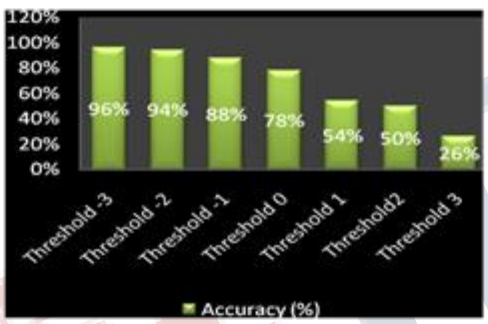

Fig. 5. GRAPH OF ACCURACY VS. MATCING CONFIDANCE THRESHOLD

• System Output

Following are the results of the real time palm recognition task: Fig. 6 shows the eigen palm output, Fig. 7 shows the average image output and Fig. 8 shows the final output of the system.

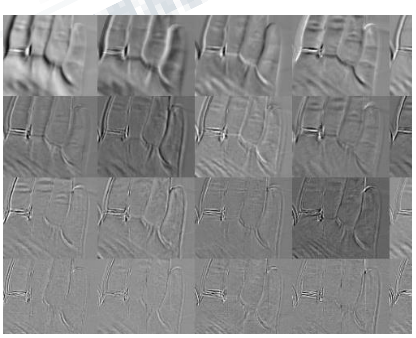

Fig. 6. EIGEN PALM OUTPUT

Fig. 7. AVERAGE PALM OUTPUT

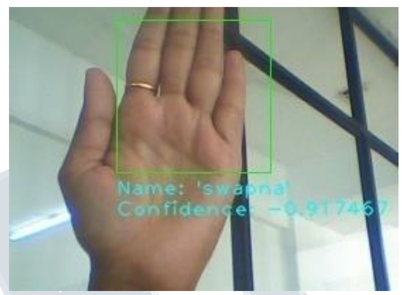

Fig. 8. FINAL OUTPUT OF PALM RECOGNITION SYSTEM

V. CONCLUSION

The system provides 78% accuracy for 0.00 MCT. It is easy to handle, very cost effective as it does not require high resolution cameras. Opencv provides a simple to use computer vision infrastructure. In the existing system if pre-processing and classification are done with fair modifications, can increase the accuracy of the existing system.

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