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An Unified Approach: Palmprint Recognition using Fused Local and Global Characteristics

Aravind Nalamothu[1] and Dr. Eswaraiah Rayachoti[2]
[1-2]School of computer science and engineering, VIT-AP, Amaravati City, India
Email: aravind.20phd7148@vitap.ac.in, eswaraiah.rayachoti@vitap.ac.in

***Abstract*— The palmprint recognition model has been attracting researchers in the last few years. Among the mage concentrations, most of the researchers focused on local feature extraction model and recognition model, or a few focused on global feature extraction model for classification purposes. In this model, the main focus was on fusion of both the local and global features of palmprint image. Various traditional methods were used to extract both the global and local features of palmprint images. The feature selection algorithm selects the optimal features from a list to include in fusion. Hausdorff distance method is used for matching purpose. For this model, two different datasets (IITD and Tongji palmprint) were used. The accuracy of the dataset was 98.91% and 98.25%, respectively. Both datasets are contactless.**

***Index Terms*— Palmprint, Biometric, Hausdorff distance, FSA, feature fusion**

I. Introduction

With the use of computer vision, machines were automated in the industrial sector to help minimize expenses, remove risky employment, enhance productivity, and carry out procedures that were unsuitable for handling physically. Automation, satellite imagery, bio-metrics, and medical diagnostics typically use imagery, which is the primary source of data storage. To access the invaluable knowledge in the photos in each of the above services, data-processing mechanisms must be included in the machines themselves. These algorithms often have pattern-recognition components that aim to draw out distinguishing elements from photos.

A pattern-recognition system's (PRS) functionality may efficiently enhance many processes, and each one of these phases might benefit from selecting the preferred technique that can be applied as per the requirements of that particular scenario. The PRS flowchart's key stages include acquisition, pre-processing with targeting ROI, extracting the ROI features, training, and judgment. In reality, these processes, which were specified earlier, were performed in order of execution; each one uses the results of the earlier phase as an input, frequently bonding its precision to that of the one before it. When the picture capture and feature extraction, the two basic processes of this type of system work together, the properties of the samples from various classes can be identified independently.

Numerous methods, including face, iris, palm, vine, finger, and DNA, act as concern of the biometric scheme implementation; The palm print features are not only easy to use and effective in extracting attributes, but they have proven to be reliable, user-friendly, and cost-effective in a broad range of security concern. The picture of the palm from the perspective from which it is taken may be easily acquired, and it is reasonably steady.

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Due to their location beneath the skin, these features have a minimal risk of falsification, are hard to duplicate, and are stable. It is reasonable to assume that each sample would possess a similar range of data, as the brobdingnagian of current palmprint recognition algorithms are based on training and testing data obtained from a very device; however, this cannot be guaranteed in the real world, as testing equipment often varies from training equipment. A system may expand palmprint recognition situations if it utilizes a mobile phone as its palmprint acquisition device, as it can acquire palmprint photographs in a short period of time without the need to purchase specialist imaging equipment.

The rest of the article follows an organized anatomical structure as previous experience gained from literature review is discussed at session 2, proposed model design is discussed at session 3, datasets and results data are discussed at session 4, and the conclusion and reference session are presented in the following order.

II. Literature Review

A Deep Feature Multispectral Palmprint Classification (DCT / DST) mechanism based on the Discrete Cosine Transform (DCT), was proposed in a paper co-authored by Aounallah (Asma), Abdallah (Meraoumia), and Hakim (Bendjenna) **Error! Reference source not found.**. This mechanism was initially used to compute individual binary palmprint images using Discrete Cosine Transformation (DCT) or Discrete Sine Transformation(DST). Subsequently, the authors fused these transformed binary images with DCT and DST **Error! Reference source not found.** and extracted the feature vector using the histogram (orientation) method. Finally, the images were classified using classifiers.

Ankit Kumar, Astha Singh, Divya Kumar, and Shiv Prakash [2] came up with a great way to detect and recognize faces using machine learning. They mainly worked on improving face detection from a dynamic frame point of view. They got the dataset from randomly chosen people who walked on a treadmill. A neural network was employed to recognize and visualize various objects, thereby facilitating the machine's ability to acquire face values. Convolution Neural Network was also employed, as well as Recurrent Neural Network-LSTM, to increase the accuracy from 97.5 percent to 98.1 percent.

Wu W. proposed a cost-effective and practical palmprint recognition system in [4]. In their palm print recognition system, an additional MOS semiconductor camera was used to obtain NIR images of the palms and veins, rather than an NIR charge-coupled device (NIR device) camera, resulting in considerable cost savings. As far as the ROI determination is concerned, they adopted the region on the thinner part of the palm (since it contains a large number of palm veins) in order to avoid palmprint effects on the picture and, hence, on the performance of the scheme. In order to enhance the accuracy of the recognition of the results, the haar wavelet decomposition and HPDLS were employed to discriminate palm-vein segment extraction. To evaluate the effectiveness of the proposed approach, experiments were performed on two databases (CASIA self-completed multi-spectrum database **Error! Reference source not found.** and CASIA public mult-spectrum database). Unfortunately, the six CASIA spectral bands were not used and only one band (850 nm).

An analysis was done in order to measure the effectiveness of DCTNet, a quick and effective deep learning feature extraction technique posed **Error! Reference source not found.Error! Reference source not found.Error! Reference source not found.**. The analysis was conducted using two public databases, CASIA and PolyU, to appraise the efficacy of the projected unimodal (and multimodal) systems. The findings of the study demonstrated that a deep learning-based feature extraction method based on DCTNet can offer comparable presentation to the most sophisticated techniques.

A method for the recognition of contactless palmprints has been proposed by Qi Zhu (author), Guangnan Xin (author), and others (author, co-author), [3]. In this method, self-paced cycleGAN is combined with self-attention modules to synthesize missing data simultaneously and minimize the influence of different imaging devices. The robust cross domain feature representativeness and recognition model are learned using self-paced cycleGAN. The dataset was collected using various smartphones.

Key motivations for this research work are: First, it is important to note that there are a variety of models that can be utilized for the collection of palm print images. As contactless palm print images from unfamiliar devices may also be utilized in real-world contexts, it is recommended to group such images using non-supervised methods and then examine the transfer learning supported identification models constructed from known data region for unfamiliar devices. And, secondly, Although most of the work has been done with Convolutional Neural Networks (CNNs) **Error! Reference source not found.Error! Reference source not found.Error! Reference source not found.Error! Reference source not found.Error! Reference source not found.**, they are still limited by the size of the convolutional kernel and cannot extract global palmprint data. Most deep learning palmprint detection techniques are mainly used for image classifying tasks. There is no research on main line properties, fine details and palmprint structure.

III. Proposed Model

The proposed architecture of the palmprint recognition system illustrated in Figure 1. Here Median filter is used in pre-processing stage over the acquired image. Then segmentation was performed over the processed image to acquire the Region of Interest (ROI). Learnable Gabor wavelet transform, Discrete Wavelet Transformation (DWT) (Figure 2 illustrate DWT features), and Principal Component Analysis (PCA) **Error! Reference source not found.Error! Reference source not found.** transformation is applied on the Feature extraction stage for extract both texture, and dimensional features.
In this system, images are acquired from an acquisition device. Pre-processing is then conducted on the images acquired. At this stage, any environmental variations are identified in the images. These variations are then corrected according to the system. At the ROI extraction phase, the Palmprint region of interest is extracted and resized to 128 x 128 px, where the system concentrates on work.

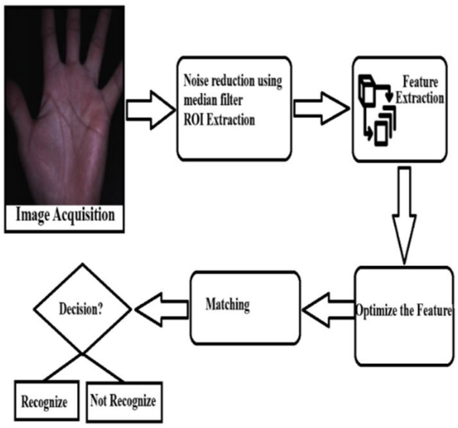

Fig 1. Proposed Architecture of Palmprint recognition model

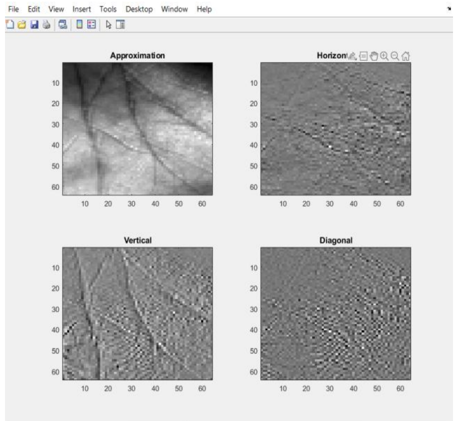

Fig.2 Single Level DWT transformation values of image

A. Feature *extraction*

In most of the models the work is done depends on the local features or Global features. Mostly on selecting of one kind of information as feature then proceeded with the model. But for here this paper is concentrating on both the works Local features as well as Global features**Error! Reference source not found.Error! Reference source not found.Error! Reference source not found.**. This model applying Learnable Gabor filter transformation over palmprint images to apply the Gabor kernel filters to extract the localized texture information from different angles. Texture feature plays an essential role in feature extraction because it is a large feature in the image. Even a single feature in the image can be extracted easily by using a texture feature. Texture features can be used for shape calculation, segmentation, image recognition, etc. Primitive and placement rules are required for extracting the texture from images.
These localized features are stored in Gabor feature set. Which contains all kinds of localized features of the image. Then performing single level discrete wavelet transformation over the image and obtained results are supplied to Principal component analysis (PCA) to extract the Global feature of the palmprint image. PCA mathematical equation is given in eq(1).

$$P_{CA} = \frac{Value - Mean}{Standarddeviation} \qquad (1)$$

B. Feature Optimization

Gabor Wavelet transformation is first performed on the palmprint image to transform it into preliminary palmprint features. Palmprint features are filtered by feature selection algorithm. Palmprint feature is multiplied by palmprint feature extracted from the extracted DWT structure and PCA structure to improve the palmprint features extracted from multi-stages. Figure 3 show the structure for extracting the prominent feature from the model.

Feature Selection Algorithm: First, the input palmprint images are converted using Gabor filter. After that, the average of input images is calculated. Second, the Gabor Wavelet transformation is applied to each of the input palmprints. The Gabor filter results in the following feature map vector: The pixels advanced than the average features are retained. The pixels with subordinate than the average features are reset to zero. This feature map then multiplies with t to manipulate the properties of component t to make the properties from component t stand out as Gt. Gabor kernel updates once for every execution of the algorithm. Remember that learnable Gabor kernel updates the kernel value according to the structure it obtains.

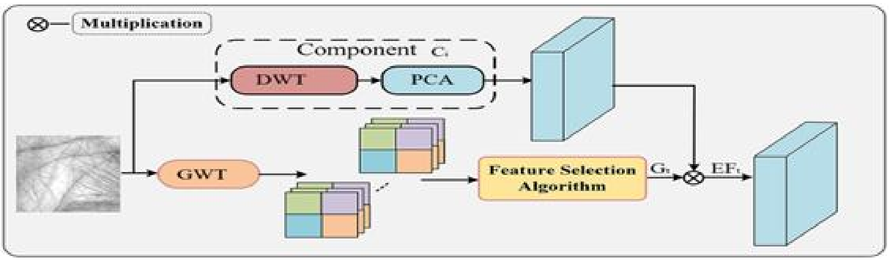

Fig. 3 Prominent feature extraction from the structure

C. Matching and *Decision*

Hausdorff distance, also known as Pompeiu Hausdorff distance, is a measure of the distance of two subsets from each other in a metric space. It converts the non-empty subset of the metric space into its own metric space. The name is derived from the names of the two mathematicians, Felix Hausdorff and Dimitri Pompeiu. Two sets are said to be close to each other if each point of one set is adjacent to a point of another set. In other words, the shortest distance between two sets is the greatest distance from one point in the set to the next point in the set. This is the shortest distance that can be forced by an adversary to a point in either set, from which the adversary must then travel to the next set. It gives the advantages for comparing the portions of one shape with another, speed and simplicity in computation and finally, for small perturbations of image it is relatively insensitive. The mathematical notation is shown in below eq (2) and eq (3):

$$H_d(I,J) = max\big(h(I,J), h(J,I)\big) \qquad (2)$$

Where I, J are two finite point sets. And

$$h(I,J) = \max_{i\epsilon I} \min_{j\epsilon J} \|i - j\| \qquad (3)$$

As long as there is only one image feature with a minimum number of portion differences, it will be considered a recognized feature. And based on that the decision will be made.

IV. EXPERIMENTS

A. Datasets used

In order to validate the proposed approach, the following experiments were conducted: Tongji University Palmprint Data Set **Error! Reference source not found.** and IIT Delhi Palmprint Database Version 1.0.**Error! Reference source not found.**

1. Tongji Uniiversity's contactless palmprint dataset:

The contactless acquisition apparatus improved in study to collected 12,000 palmprint images from 600 different palmprints for the use of Tongji University's contactless palmprint dataset**Error! Reference source not found.**. The 300 participants included 235 individuals aged 20-30 and the remaining 235 individuals aged 30-50. Of the 300 participants, 192 were male and 108 were female. Two separate sessions were conducted to collect both left and right sample images. Approximately ~2 months interval time maintained in collection of First and second sessions. Each participant was provided with 10 images per palm during each session, resulting 40 images collected from each participants two palms.

2. IITD Contactless Palmprint Database:

The IIT Delhi Touchless Palmprint Image Database **Error! Reference source not found.** is mainly made up of hand images taken from students and staff members at the Indian Institute of Technology (IIT Delhi) between

January 2006 and July 2007. The images were taken with a digital camera equipped with a CMOS sensor and stored in a bitmap format, and the database is made available to researchers free of charge. The database consists of left and right palm print images from over 230 individuals, all aged 14-56, who have donated at least 5 palm print samples from each hand. With the collections of database contains 2600 palmprint images, and the images are of a high quality of 800 X 600 pixels. The sample images from both datasets are displayed in Figure 4 and in Table 1 displayed the dataset information.

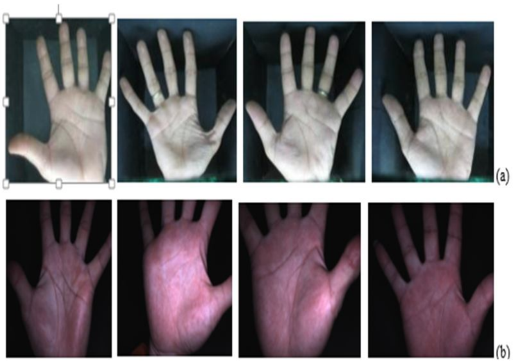

Fig 4 (a) IIT Delhi Palmprint database sample images (b) Tongji university database sample images

Datasets were broken down into training and testing datasets by 4:6 ratio. From tongji dataset, 4800 images were used for training and the remaining 7200 images were used for testing. Similarly, from the dataset of IIT Delhi, 1040 images were used to train and the remaining 1560 images were used to test.

TABLE I DATASETS INFORMATION

Databases	**IITD**	**Tongji**
Collection	Contactless	Contactless
No. of categorize	460	600
No. of representative per categorize	~5-6	10
Total number of representatives	2600	12000

To demonstrate the effectiveness of the palmprint recognition technique proposed, Here compared several cutting-edge palmprint recognition techniques that have been tested against the Tongji Palmprint dataset and IIT Delhi Palmprint dataset.

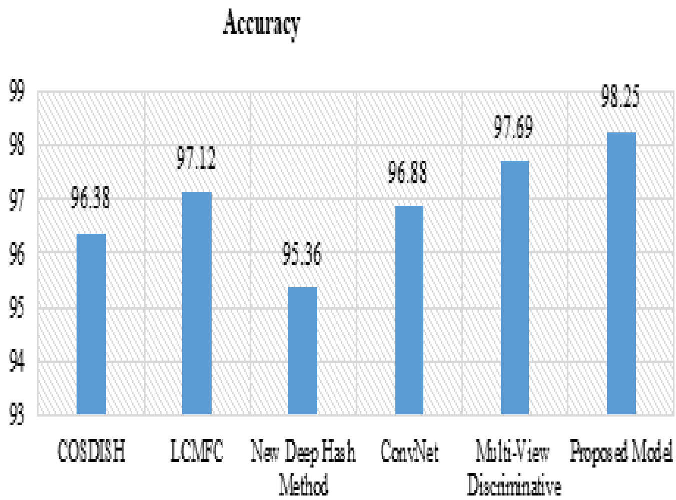

Fig. 5 Comparison of Accuracy of different models with the proposed model over Tongji Palmprint dataset

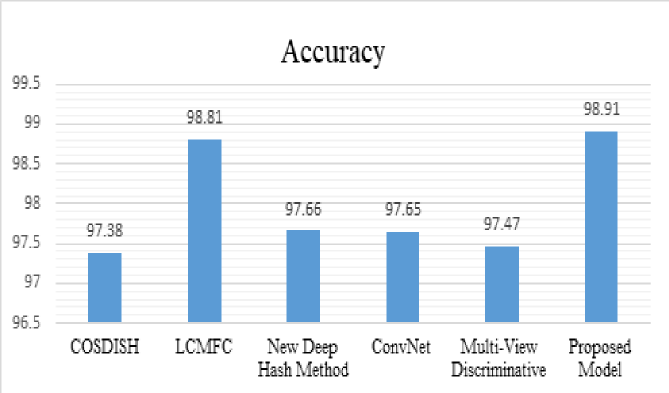

Fig 6. Comparison of Accuracy of Different models with the proposed model over IIT Delhi Palmprint dataset

Based on the results obtained, the method presented in this paper achieved better performance compared to others.

V. Conclusion And Future Enhancement

In traditional palmprint identification, it is difficult to extract and select features, and the process of extracting features, selecting features, and selecting a classifier takes a long time. The convolutional neural network has better nonlinear fitting capability than classical algorithms, but it has limitations due to the kernel size and the inability to extract global palmprint information. The proposed model suggests that by combining local feature of an image and global feature of the same image, results are obtained with less computational operations and limited time. The mechanism achieves 98.91 percent for IITD palmprint dataset, and it achieves 98.25 percent for Tongji palmprints dataset. However, the proposed technique has the downside that the fusion of global feature and local feature may undergo the performance due to environmental effects. The model is consuming very little time to recognize. Future work will be planned to overcome the drawbacks and create a robust model suitable for contact-oriented as well as contactless applications.

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