International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8 Issue-6, March 2020

Genetic Algorithm Based Gabor CNN For Palmprint Recognition

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Abstract*: In the field of biometrics, palmprint recognition has received great interest and made tremendous progress in the past two decades. In palmprint recognition, the important step is to extract the discriminative features from the image and compare it with templates for identification and verification tasks. In this paper, a new genetic-based 2D Gabor filter with the Convolutional Neural Network is presented. The scale and orientation details captured by Gabor filters are optimized based on central frequency, which is determined based on genetic algorithm fitness function. The proposed technique is implemented on four publicly available palmprint datasets- PolyU, CASIA, IITD, and Tongji. Experimental results confirm that the proposed technique achieves better accuracy when compared to Palmnet.

***Keywords* : Gabor Filter, Palmprint recognition, CNN.**

I. INTRODUCTION

Over the last two decades, biometric security is an emerging tool for security purposes in many applications. Nowadays Government and private industries are using biometrics for security measures. Several biometric characteristics, such as fingerprint, iris, face, palmprint, gait, etc. have been widely used based on the aptness of the applications. In recent years, Palmprint recognition received wide attention from researchers. Comparing to other biometric traits, palmprint has strong stability, low distortion, and high uniqueness. Palm features, including flexion creases, wrinkles, ridges, and minutiae are located on a palmar side of a hand and are considered to be permanent and unique to an individual. The Palmprint system may be classified as touch based and touchless palmprint system. Due to hygienic reasons, users want to use touchless palmprint as a biometric. touchless palmprint images are acquired through a less constrained environment when compared to touch-based methods. As a result, the images of touchless palm print show higher local variations in terms of scale, rotation, translation, and also with illumination; thereby increase in their intra-class variations leads to reduce recognition accuracy.

To obtain better recognition accuracy for the touchless palmprint images several methods use local texture descriptors based approaches that are invariant to scale, rotation, translation, and illumination. Local texture descriptors based approaches extract local details related to the orientation of the palm lines on the palm to compute a biometric template. However, these techniques require handcrafted processing techniques for extracting the features, using parameters whose optimum values may vary for each dataset depending upon the quality and resolution of the input palmprint images. Various biometric approaches are currently being developed using Convolutional Neural Networks (CNNs) and Deep Learning (DL) based on its ability to extract information from the noisy data, adjust to the biometric samples obtained using different capturing devices that attain high recognition accuracy in a less-constrained environment. Several CNN based techniques are presented in the literature. One of the major drawbacks of these approaches is that it uses general-purpose filtering techniques to obtain the features instead of using palmprint specific filters. In most of these techniques, the input parameters are not optimized. In our proposed system, a novel genetic-based adaptive Gabor CNN that tunes the parameters automatically based on the fitness function described in section III.

The remainder of the paper is organized as follows. In Section II, a brief review of the important techniques for touchless palmprint recognition is explained. Section III discusses genetic based Gabor CNN palmprint recognition. Section IV describes the experimental results. Finally, in Section V conclusion has been incorporated

II. RELATED WORKS

The existing methods for contactless palmprint recognition can be categorized depending on the dimensionality of the collected inputs as two-dimensional (2-D) or three-dimensional (3-D). In this paper we focused only on 2-D images. Palmprint based recognition techniques can be categorized into seven different types 1) texture-based[1], which represents the rich features as compared to the abstract labels. 2) line-based[2], uses principal lines and wrinkles of the palmprint that can be used to represent low resolution images. 3) subspace based learning, which characterize the palmprints principal components using a small feature sub space; 4) correlation filter-based, which uses the correlation filter to construct a sharp peak value when it filters a given sample. 5)

Manuscript received on March 15, 2020.
Revised Manuscript received on March 24, 2020.
Manuscript published on March 30, 2020.
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Local descriptor-based approach extracts and encodes local features of the palmprint using a descriptor; 6) orientation coding-based approaches extracts and encodes orientation features of the sample palmprint.7) CNN-based approaches extract the features of palmprint using convolutional neural networks.

Numerous methods for palmprint feature extraction and its recognition is mentioned in [3]. Recently, a methodology based on coding scheme [4-8], local texture descriptors [9-11] and CNN[12,13,14] demonstrates excellent recognition accuracy for contactless palmprint recognition. So this work focuses only on these three types.

Coding-based approaches generally consist of applying a set of filters to a palmprint input image. The obtained result of the filters is quantized based on magnitudes or phases. Finally, the encoded results are computed and stored as a biometric template. Then, the resulting templates are compared using global matching techniques which is based on Hamming distance[4]. These approaches can be categorized based on single and multiple orientations. Single orientation based approaches consider only the maximum significant orientation for each image region. Some of the single orientation approaches are PalmCode[4], FusionCode [5],Competitive code[6], Double-Orientation Code[7], RLOC [8] etc. PalmCode encodes the phase of Gabor filter responses to represent binary features. FusionCode further improves PalmCode by encoding only the maximum magnitude of filter responses. Competitive code encodes minimum filter response using multiple Gabor filters with 6 different orientations based on angular distance. Double-Orientation Code uses the most two dominant filter responses as the dominant orientation feature. RLOC uses twelve Radon- based filters to get the dominant directions of the palmprint.

The methods based on multiple orientation extracts features from a biometric template by describing several orientations for every local region of the palmprint image. BOCV[9], Neighboring Direction Indicator (NDI)[10], Robust Competitive Code method, etc. are based on multiple orientation techniques. The major drawback of coding-based techniques is that the local variations and translations are not accounted while comparing biometric templates.

Local texture descriptor based techniques extract the intensity value of every pixel to compute the histogram for every local region. Then concatenate the blockwise histograms to create one dimensional feature vector for the biometric template. Scale-Invariant Feature Transform (SIFT), Histograms of Oriented Gradients (HOG), Local Binary Patterns (LBP), Local Directional Patterns (LDP), Local Line Directional Pattern (LLDP) and Local Tetra Patterns (LTrP) descriptors[11] are recent local texture based descriptors. The feature extraction, as well as the tuning parameters of these approaches, are computed manually. Further, the computational complexity is high.

Convolutional Neural Network extracts features from palmprint images and based on distance measure or a trainer classifier compares biometic templates. Liu, et al.[12]uses eight-layered network structure called 'AlexNet' for palmprint feature extraction. Using CNN-F architecture, Sun et al.[13] extracted the features and assessed the convolutional features vector from the network structure. Zhong et al.[14] presented a Siamese-like network architecture that directly derives the similarity index of two palmprints inputs using Two parameter-sharing VGG-16 networks and achieves highly accurate recognition outcome. Meraoumia et al.[15] proposed an unsupervised PCA-based CNN that extracts the features from palmprint images, and a trained SVM classifier is used for classification. Genovese et. al proposed PalmNet[16], which uses Gabor-PCA CNN based adaptive filters to extract discriminative features from the palmprint images and Knn classifer is used for classification which achieves high recognition outcome.

III. METHODOLOGY

In this section detailed description about preprocessing, Convolutional Neural Network training and Genetic Algorithm based Gabor CNN is explained.

A. Preprocessing

In the preprocessing step, Region of Interest (ROI) is extracted from a grayscale palmprint input image. This process can be split into three steps: i) segmentation of Hand, ii) Extraction of valley points iii) Computation of ROI. Figure 1 shows a snapshot of an extracted ROI from a touch less palmprint image. This sub-section focuses on hand segmentation techniques built on gray-level thresholding methods and edge detection. Initially, the image is converted from RGB to grayscale. Then the background is removed and the hand contour is extracted using Otsu thresholding method and Kirsch edge detector technique [17]. From the hand contour, the local minima intersections in between the index-middle and ring-little fingers valley points are analyzed using the procedures discussed in[18]

Finally, ROI is computed by setting up a reference system based on the obtained valley points [5]. The ROI is resized to the dimensions of u × v pixels, normalized by subtracting the mean value.

B. CNN Training

The proposed CNN has 3-layers which are configured as follows: convolutional layers (L1 and L2) and a binarization layer (L3) is depicted in Figure-1

- L_0: Input layer consists of u×v dimension, corresponding to palmprint ROI Size.
- L_1: First convolutional layer, which is consists of $m_1$filters. Each filter processes the input image; and produce$m_1$images of dimension u×v. The filters central frequencies are tuned based Genetic algorithm.
- L2: Second convolutional layer, consists of m_2 filters. Each filter processes the m_1 images and produce m_1m_2 images with dimension u×v. In this layer also Genetic algorithm is used to tune the central frequencies.
- L3: It is a Binarization layer apply the function f(y) = bin(y) as in(1) to each pixel of the m_1m_2 images output where bin(y) is defined in the following equation:

$$bin(y) = \begin{cases} 1 & if\ y > 0 \\ 0 & else \end{cases} \quad (1)$$

The output of L3 layer composed of $m_1m_2$binary images with the dimensions of u×v. The purpose of using this layer is to allow the output of L2 to be minimized by combining many outputs into single decimal numbers.

Gabor filters

Gabor filters are used to extract features in palmprint recognition. Gabor function is a sine function modulated by Gaussian function, which can be used to extract local frequency domain features in a given region of the image. We used 2-D Gabor filter has the following general form as in (2): The Gabor filter is fundamentally a Gaussian (with variances σ_x and σ_y along x and y-axes respectively) modulated by a complex sinusoid (with centre frequencies U and V along x and y-axes respectively) described by the following equation

$$G(x,y,\theta,u,\sigma) = \frac{1}{2\pi\sigma_x\sigma_y}\exp\left[-\frac{1}{2}\left\{\left(\frac{x}{\sigma_x}\right)^2+\left(\frac{y}{\sigma_y}\right)^2\right\}+2\pi j(Ux+Vy)\right] \quad (2)$$

Gabor Convolutional Networks (GCNs) is a CNN which uses bank of Gabor orientation filters (GoFs). A GoF is a steerable filter that produces the enhanced feature maps by learning discriminative information present in the palm print ROI image[19]. Gabor filters are of u directions and v scales. To incorporate the steerable features into the GCNs, the orientation details are encoded in the learned filters, and also the scale information is embedded into different layers. Due to the scale and orientation details captured by Gabor filters in GoFs, the equivalent convolution features are enhanced.

The filters in layers L1and L2 are of variable sizes that are configured by the use of unsupervised learning methods. In this work Gabor filters are used, which are adapted using Genetic Algorithm

C. Filter tuning based on Genetic Algorithm

Genetic Algorithm optimization works by representing the possible solutions as the chromosomes. In every generation, a new set of chromosomes are produced using the chromosomes in the population pool by crossover and mutation operations. After reproduction, using fitness function both new and old chromosomes are evaluated and only the strong chromosomes (high fitness) are selected in the next generation's population pool. By repeating this process, the chromosomes in the population pool move closer to an optimal solution. The iterative process terminates on some convergence criteria, i.e. reaching the maximum number of generations, or when little to no change in the population's fitness is found. In our application, we utilize multi-objective optimization since there are two main objectives that need to be achieved. The first objective is to minimize the number of the filters in the filter bank, while the second objective is to maximize the discriminative power of the filter bank. The data driven filter bank is dependent on the data nature. The data with visual inspection makes the design of filter bank difficult. There is commonly used two methods by the researchers. In the first method large number of filters in a filter bank which covers all information based on scale and orientation. This leads to a rise in cost for computation because of more filters than required, which is a drawback. The second method is to determine the best parameters for the filter bank by creating a set of experiments. Though this method is labor-intensive, the benefit is that the filter bank can be created efficiently.

In the proposed approach we obtain U and V values using Genetic Algorithm techniques with few samples of the dataset. The tuned parameter is used in the Gabor filter inside the CNN.

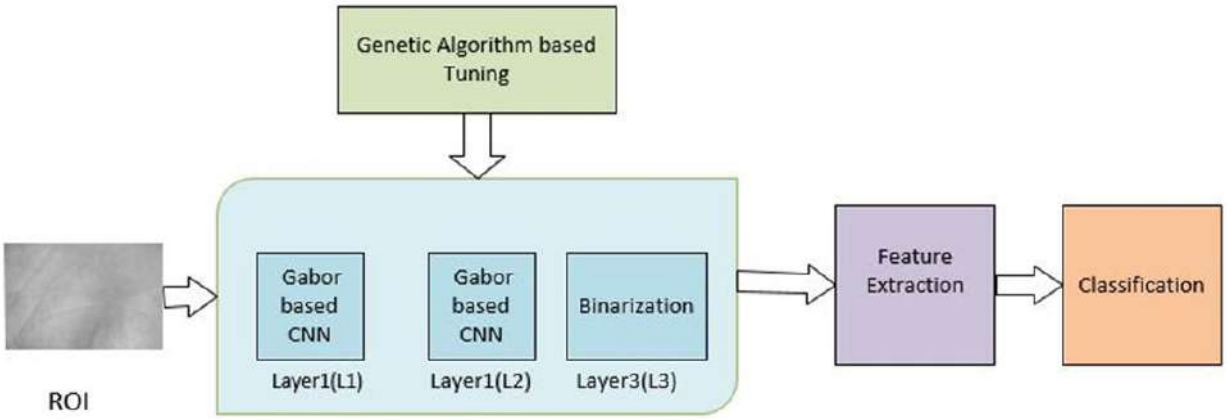

Figure 1 : Proposed Gabor CNN with Genetic Algorithm based tuning

Given below are steps for Optimization of Gabor convolution kernels which are summarized as follows:

(1) An initial population of fixed size 2k is generated randomly where k represents the number of Gabor convolutional kernels. Chromosomes in the population correspond to the standard deviation of Gaussian σ and the central frequency of sinusoidal grating U and V along x and y axis respectively of Gabor kernels.

(2)The fitness value of each individual of the initial population related to Gabor kernels is computed.

(3)The successive generation, including the fittest individual from the predecessor generation, is generated by selection, mutation and crossover operations.

(4)Each individual in the new generation is evaluated and the optimum Gabor kernels related to one individual is retained.

(5)If the target is achieved, or maximum generations are reached, the best performing individual related to Gabor kernels is returned as the result; otherwise return to step (3).

D. Classification

During the identification process, the features of the test Palmprint image, equivalent to each person, is analyzed by CNN learning. During the process of identification, the test Palmprint image features of each person are analyzed using CNN learning. Then the similarity/dissimilarity between two feature vectors is computed using simple k-Nearest Neighbors classifier based on the Euclidean distance.

IV. EXPERIMENTS AND RESULTS

This section presents the database used to conduct the experiments and the results obtained. All the experiments are carried out using a machine with 1.70 GHz CPU, 4G memory with Matlab R2018b.

A. Databases

The proposed method is experimented and evaluated on four publically available databases, which is, CASIA [11], PolyU II [10], IITD [12],Tongji Contactless Palmprint databases. CASIA Palmprint Database comprises 5502 palmprint images captured from 312 users. IITD palmprint database comprises of 2601 images captured from 460 palms belonging to 230 users. PolyU II database consists 7752 grayscale palmprint an image belongs to the 193 persons from 386 palms. Tongji database contains 6000 images belongs to 600persons. To assess the performance of our proposed method, we choose 2900 images with 290persons from PolyU II database, 2400 palmprint images with 300 persons from CASIA database, 1250 images with 225 persons from IITD database and 5500 images with 560 persons from Tongji databases are chosen for testing in experiments.

B. Extraction of ROI and the preprocessing result

Region of Interest comprises of the rich palmprint image textural information, using the method described in the part-III is used to extract the ROI from all of the four databases, then normalized to a size of 128×128 pixels. The results are shown in Figure-2.

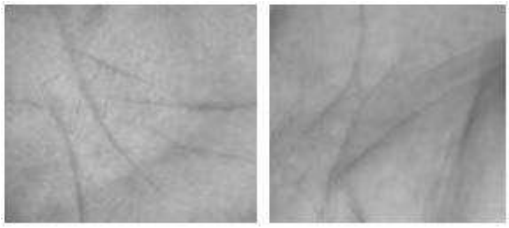

Figure 2:Palmprint ROI images of IITD and CASIA

C. CNN Feature extraction and matching

To evaluate the accuracy of the proposed technique, we partitioned the data set into two parts one part is used for the training which contains approximately 60% of the ROI images and remaining images are used for testing. For each identification task, there is a need to determine several parameters. To tune the parameters, we collected a small set of palmprint datasets using the same device and parameters are determined. For every identification method, the tuning parameters were empirically adapted in a greedy manner and best parameter values are chosen so that they could lead to a high recognition rate. Figure-3 shows the accuracy obtained using the four databases by varying the filter size values. Initially, we find the optimum filter size by varying it manually to obtain the best result. The experiment is done in comparison with work carried out by Genovese et. al [16] the parameters of the CNN is shown in the table-I.

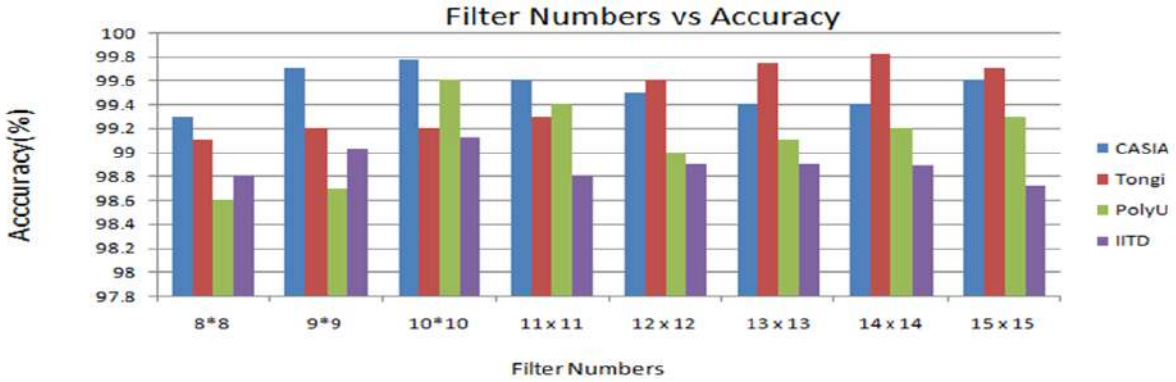

Figure 3: Filter numbers vs. accuracy

Table- I: summarized parameters of the CNN compared with palmnet[16]

Network	*Parameters*	*Value(s)*	*Description*
	u, v	128,128	Horizontal and vertical sizes of ROI image
	h1,h2	35,35	Fixed scale Gabor filters dimension
	μ	0.11	Fixed Gabor filters wavelength
	σ	5.6179	Standard deviation
	m_1	15	Number of filters in L1
	m_2	15	Number of filters in L1
Palmnet-Gabor	F	10	Number of fixed-scale Gabor filter
	A′	5	Number of adaptive multi-scale Gabor filter
	S	10	Number of most frequent orientations
	a_0	2	Scaling factor of the adaptive Gabor filter
	r	1	Aspect ratio of adaptive Gabor filter

The proposed technique is compared with Alexnet, PalmNet-Gabor techniques. In Alexnet 8 layers network structure is used for feature extraction. Hausdorff distance is used to measure the feature matching[12]. In PalmNet-Gabor method Gabor filter is applied in CNN and Euclidian distance is used for matching[16]. The experimental result shows that the proposed approach performs better in terms of accuracy as shown in Table-2.

Table 2: Accuracy (%) of the Proposed Method Compared with other recently proposed techniques

	CASIA	Tongi	PolyU	IITD
Alex Net	99.08	99.37	96.43	96.22
PalmNet-Gabor	99.77	99.80	99.02	99.06
Proposed approach	**99.79**	**99.83**	**99.10**	**99.12**

V. CONCLUSION

In this paper, we presented a Genetic algorithm based Gabor filter with Convolution Neural network for touchless palmprint recognition system. The scale and orientation details are captured using Gabor filters and network parameters are adaptively set based on the genetic algorithm fitness function based central frequency and the filter size is adapted according to the input dataset. The proposed technique is experimented with four publicly available datasets- PolyU, CASIA, IITD, and Tongji. The experimental result shows that the proposed genetic-based CNN performs better in terms of accuracy as compared with the state of art methods.

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