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Multi-modal Iris Recognition System based on Convolution Neural Network

Gajanan Choudhari, Rajesh Mehra, Shallu

Abstract: ***Iris is most promising bio-metric trait for identification or authentication. Iris consists of patterns that are unique and highly random in nature .The discriminative property of iris pattern has attracted many researchers attention. The unimodal system, which uses only one bio-metric trait, suffers from limitation such as inter-class variation, intra-class variation and non-universality. The multi-modal bio-metric system has ability to overcome these drawbacks by fusing multiple biometric traits. In this paper, a multi-modal iris recognition system is proposed. The features are extracted using convolutional neural network and softmax classifier is used for multi-class classification. Finally, rank level fusion method is used to fuse right and left iris in order to improve the confidence level of identification. This method is tested on two data sets namely IITD and CASIA-Iris-V3.***

Index Terms: ***Convolutional Neural Network, Softmax classifier, Iris Recognition, Bio-metric***

I. INTRODUCTION

Iris recognition system provided a trustworthy and secure environment for its users. A major problem is its deployment in large scale application. One of large scale application, which brought diverse population, is inclusion of iris trait in AADHAR card in India. Iris recognition system is evolving as most powerful bio-metric identification system [1]. Compared to other biometric trait, iris trait has number of advantages such as iris is in annular region of pupil and sclera which is completely protected from external environment, no physical contact is required for identification or authentication this makes system hygienic, stability over life time of user and high degree of randomness in pattern that differentiates the identities of twins and even right and left eye of same person. Apart from these advantages, iris acquisition makes the problem of capturing irrelevant parts such as specular reflection, eyelashes and eyelids. This influences the localization accuracy of iris in turn recognition rate of overall system. The unimodal system uses only one of biometric trai for identification. This may suffer from noise present in image , intra-class variation , inter-class variation and non-universality [2]. The multimodal system has ability to overcome this limitation by combining evidences from both iris and solves the problem of non-universality. Convolutional neural network has automated the feature extraction process without any domain knowledge and also given outstanding results over Texture code [3] , Discrete Wavelet transform (DWT) [4], Scattering Transform [5] , Shift Invariant Feature Transform (SIFT)[6] and Discrete Cosine Transform (DCT) [7]. Now a much attention is focusses in designing CNN model for automatic feature extraction and suitable classifier for classification purpose [8]. First contribution made by Daugman in implementation of complete iris recognition system. The 2D Gabor filter is used for feature extraction and Hamming distance is used for classification [9]. Rai et al.[10] used Daubechies wavelet transform to extract textural features. This method reduced the number of features to be stored for each template. Saiyed et al.[3] used texture code matrix to compute the co-occurrence matrix which further used in computation of features. Part of iris is used to avoid the occlusion by eyelashes and eyelids. Constrained Circular Hough Transform (CCHT) is used for pre-processing which reduced complexity. Minaee et al.[5] proposed scattering transform and textural features of iris images and minimum distance classifier is used for classification. Dhage et al.[11] provided use of combination of Discrete Wavelet transform (DWT) and discrete cosine transform (DCT) for feature extraction. The Euclidean distance classifier is used for classification. Rathgeb et al.[6] used general image descriptor as SIFT(shift invariant feature transform) for feature extraction. This work mainly focuses on recognition accuracy of iris recognition. Alaslani et al.[8] used pre-trained Alex-net models of convolutional neural networks architecture for feature extraction. Circular Hough transform is used in pre-processing of images. Support Vector machine is used for the classification purpose. Alaa S. Al-Waisy et al.[12] proposed a deep learning approach for Iris Recognition System. This method has given outstanding results. The system made multimodal by fusion ranking method. Iris features are extracted using scratch convolutional neural network architecture. Here many network configurations are tested for high recognition rate. This method has addressed the problems of non-universality, inter-class variation and intra- class variation. But as single CNN architecture has given slightly different recognition rates on both right and left of same database. In this work, CNN architecture is designed from scratch for feature extraction. The network learning is done by using back propagation algorithm with Adam optimization technique. The Adam optimization doesn't provide monotone convergence but reaches more global minimum in less computations. Combination of CNN and softmax classifier is used for automatic feature extraction and multi class classification respectively. The other training strategies such as dropout and data augmentation included to avoid the over fitting problem.

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The main contribution of this paper is: 1) An improved Multimodal Iris Recognition System is proposed. The rank level fusion method is used to fuse the right and left iris.
2) The effect of Adam optimization is observed which resulted in improved Identification Rate and good generalization ability.
3) An attempt is made to use single CNN architecture for both right and left iris.
This is tested on two publically available datasets collected under different conditions: CASIA-Iris-V3 and IITD.

II. DATA SET

The Two Iris databases used for implementation are IITD and CASIA-Iris-V3. In the IITD database consists of 224 subjects include 176 males and 48 females. Each subject's 5 iris images of left and right are taken. The camera used for capturing the images is JIRIS, JPC1000 and digital CMOS camera. It consists of total 2240 images. In case of CASIA-Iris-V3 database, it consists of 249 subjects out of which only 120 subjects used for testing. Each subject's 7 iris images of left and right are taken. Here 7 images of each iris is available for 120 subjects. The camera used for capturing iris images is self-developed close up camera. The more details of iris database are given in **Table 1.**

TABLE I. IRIS DATA SET

Database	IITD	CASIA-Iris-V3
No. of persons	224	120
No. of Images	2240	1680
Samples	5 left and 5 right	5 left and 5 right
Size	320X280	320X240
Format	BMP	JPEG
Camera	JIRIS,JPC1000 and digital CMOS camera	Self-developed close up camera

III. PROPOSED IRIS RECOGNITION SYSTEM

Initially efficient pre-processing is employed on iris images to detect iris from other unwanted part such as pupil, scalar, specular reflection, eyelids and eyelashes. After detection of iris region, the iris is transformed from Cartesian co-ordinate system to polar co-ordinates by Daugman's Rubber sheet model. A fixed dimension images are generated out of this process. This dimensional reduction reduces computational burden on CNN. The discriminative features are extracted using scratch CNN configurations design. CNN acts as automatic feature extractor without domain knowledge. Softmax classifier is placed at the top of CNN to generate probabilistic matching score. The matching scores of right and left iris are obtained using fully connected layer at the end. Finally fusion ranking method such as Borda Count method is used in order to make system multi-modal. The overall proposed Iris Recognition System is as depicted in figure 1.

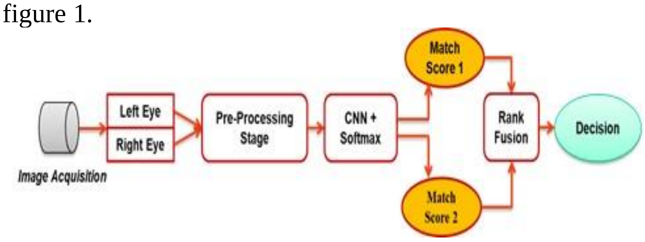

Fig. 1. Multi-Modal Iris Recognisation System

A. Iris Localization and Normalization

Iris localization is done using efficient and fast localization method as proposed in paper [13]. In this method, initially specular reflection detected and reflection mask is created out of it. These specular reflection spots are pained using reflection mask. An image enhancement employed using 2D Gaussian filter and histogram equalization to reduce computational cost of Circular Hough Transform (CHT). Finally, fast and accurate eyelid detection algorithm is used to detect the upper and lower eyelids. This algorithm uses the anisotropic transform with Radon transform to fit the eyelids as straight lines as shown in Figure 2. After localization method, in order to get the images of required size iris normalization is done. This removes the dimensional inconsistencies occurred due to pupil contraction, imaging distance and elastic distortion. Using Daugman's rubber sheet model the iris image transformed from Cartesian co-ordinate system to polar co-ordinate system as shown in Figure 3. The mapping of pixels is done from normalized images (p,q) to non-centric (r, θ) where r interval [0,1] and θ ranges from [0, 2π].The mapping is mathematically represented as

$$I(x(r,\theta),y(r,\theta))\rightarrow I(r,\theta)$$
$$x(r,\theta)=(1-r)\ xP(\theta)\ rxl(\theta) \qquad (1)$$
$$y\ (r,\theta) = (1-\ r)\ \ yP(\theta)\ ryl(\theta)$$

Where , I(p,q) is pixel intensity value at co-ordinates (p,q) and remaining parameters are co-ordinates r along θ direction[12].

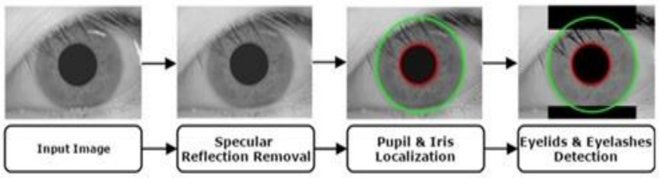

Fig. 2. Iris Localisation [2]

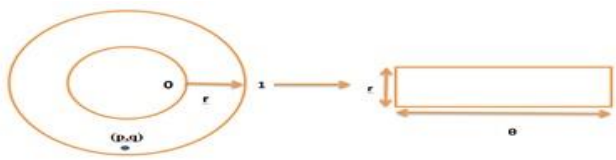

Fig. 3. Daugman Rubber sheet model for co-ordinate mapping

B. CNN Architecture Design

The CNN architecture is dependent on input image size. From literature, it seems that there is no theory available for design of CNN architecture for given application. In this paper two CNN architecture designs are proposed for input image size **64X64** and **128X128**. In both architectures, first Convolution layer is with filter size of **3X3** is used. The number of filters is kept small at initial layer and increased in successive layers. The number of filters kept increasing in order to get high level features of iris images. Then batch normalization layer is used to normalize the output of convolutional layer.
This layer is kept after each convolutional layer. The

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TABLE II. CNN ARCHITECTURE FOR IMAGE SIZE 64X64

Layer Type	No. of Filters	Feature Size	Kernel Size	Padding	Stride
Input Image		64X64X1			
Convolutional Layer 1	6	64X64X6	3X3	1	1X1
Batch Normalisation					
Leaky Relu					
Max pooling layer		32X32X6	2X2		2X2
Convolutional Layer 2	32	28X28X32	5X5	0	1X1
Batch Normalisation					
Leaky Relu					
Max pooling layer		14X14X32	2X2		2X2
Convolutional Layer 3	128	12X12X128	5X5	1	1X1
Batch Normalisation					
Leaky Relu					
Max pooling layer		6X6X128	2X2		2X2
Convolutional Layer 4	512	1X1X512	6X6	0	1X1
Batch Normalisation					
Leaky Relu					
Dropout (0.5)					
Fully Connected Layer		(120/224)X1			
Softmax Layer					
Classification Layer		(120X224)			

TABLE III. CNN ARCHITECTURE FOR IMAGE SIZE 128X128

Layer Type	No. of Filters	Feature Size	Kernel Size	Padding	Stride
Input Image		128X128X1			
Convolutional Layer 1	6	128X128X6	3X3	1	1X1
Batch Normalisation					
Leaky Relu					
Max pooling layer		64X64X6	2X2		2X2
Convolutional Layer 2	16	62X62X16	3X3	0	1X1
Batch Normalisation					
Leaky Relu					
Max pooling layer		31X31X16	2X2		2X2
Convolutional Layer 3	64	27X27X64	5X5	0	1X1
Batch Normalisation					
Leaky Relu					
Max pooling layer		13X13X64	2X2		2X2
Convolutional Layer 4	256	9X9X512	5X5	0	1X1
Batch Normalisation					
Leaky Relu					
Convolutional Layer 5	512	1X1X512	9X9	0	1X1
Batch Normalisation					
Leaky Relu					
Dropout (0.5)					
Fully Connected Layer		(120/224)X 1			
Softmax Layer					
Classification Layer		(120X224)			

batch normalization layer is used after each convolutional layer to reduce the feature co-variance shift. This resulted in speeding up in network learning. Batch normalization also provides regularization to network to some extent. The activation function used is Leaky Relu. This avoids the problem of dead neuron in Relu activation which do not take part in back propagation. The Max-pooling layer reduces the spatial size of features generated in convolutional layer. The number of filters in max-pooling layer is kept same as that of convolutional layer. The size of filter used in max-pooling is fixed to **2X2**.The stride for max-pooling layer is chosen 2. The max-pooling layer provides translational and rotation invariance. Only one fully connected layer used at the top of network. To control the spatial size padding is used. The network configurations are as shown in Table II and Table III. Note Number of classes for IITD is 224 and CASIA-Iris-V3 is 120.

A. Training Methodology

In this work, in order to reduce over fitting problem and improve generalization ability of network, the training techniques and strategies are chosen. These are given as follows:

1) *Data Augmentation*

The Deep Neural Network requires large data sets to avoid over fitting problem. This also improves the classification at end. This method is used to artificially enlarge the data set. The methods include random crop, intensity variation and flipping . Initially rectangular image is converted in square image. Then five images are cropped out of square image corresponding to 4 corners and one central. After words the square images horizontally flipped and again 5 images are cropped. The total 10 images generated for each input image. . Here two patch sizes are extracted from original image size of 64X64 and 128X128. The augmented data used as provided by author Alaa S. Al-Waisy [2].

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2) Dropout Method

During learning of network, in each iteration, few nodes are removed with 50% probability. These dropped nodes do not take part in learning. This result in a thinned network is generated that shares the weights. This method provides the regularization to network. In this work, dropout method is applied to fully connected network because it includes more weights which are vulnerable to over fitting. The dropout method helps in learning strong features [14].

3) Adam Optimization

It is variation of combination RMSProp and SGD with momentum. In this optimization method, keeps a track historical first moment and second moment of gradients is kept. The second moment is exponential moving average of gradients. This solves the problem of zero initialization of bias. The learning rates are initialized to 0.001. The suggested default settings for the tested machine learning problems are $\alpha = 0.001$, $\beta 1 = 0.9$, $\beta 2 = 0.999$ and $\varepsilon = 10^{-8}$. The final parameter update is given by

$$\theta_t = \theta_{t-1} - \frac{\alpha}{\varepsilon + \sqrt{\tilde{v}_t}}\, \tilde{m}_t \tag{2}$$

Where α is learning rate, ε is small number to prevent any divide by zero in the implementation, θ_t is final parameter update , $\hat{v}_t$ is bias corrected second row moment estimate and $\hat{m}_t$ is bias corrected first moment estimate. This is alternative optimization techniques to SGD with momentum. This optimization method combines the benefits of RMSprop and AdaGrand optimization methods. The more details on this optimization is given in [15].

D. Softmax Classifier

This classifier is useful in multi class classification. This classifier generates a vector of probability distribution of input set with each class. This is probabilistic model of classifier. The strong prediction values will be closer to 1 and weak prediction values are near to 0. The cost function used by softmax layer is cross entropy function [16] . Let **K** are classes and **n** training sample labels. The estimate probability $P_h(x_i)$ is given by

$$P_h(x_i) = \frac{1}{\sum_{j=1}^{k} e^{h_j^T x_i}} \begin{bmatrix} e^{h_1^T x_i} \\ e^{h_2^T x_i} \\ \vdots \\ e^{h_k^T x_i} \end{bmatrix} \tag{3}$$

Where h ranges from 1 to K are parameters and learned back propagation algorithm. For input x_i , softmax will produce a k dimensional vector whose sum is 1, where each vector element is estimated probability based on input feature.

E. Hyper-Parameter Selection

Input data is divided in 80:10:10 as training, validation and testing respectively. More information on effect of data splitting is given in [17] . The architecture or configuration is designed and trained with training set, after each epoch the validation data is used to calculate cost value and validation error rate. The training procedure is done by using back propagation algorithm with adaptive moment estimation optimizer. Early stopping procedure is used to stop leaning as soon as high accuracy is reached at minimum validation error. At last validation data is used to calculate the accuracy of configuration or architecture which further calculate identification rate. Identification rate is used as objective function used to maximize during the learning process. The learning rate is set to 0.001. The batch size used is 128. For Adam optimization techniques parameter are set to $\beta 1 = 0.9$, $\beta 2 = 0.999$ and $\varepsilon = 10^{-8}$.

F. Rank Level Fusion

Here rank level fusion method is used at classifier to generate a ranked list of possible match score. These ranked lists are taken in to account for final decision. Suppose employed classifiers are **M** and registered individuals are **P** . The rank **Rx,y** is rank assigned by **X^th^** classifier to registered **Y^th^** person. The fusion methods are used to find the consensus rank **Rf**. In this paper, Borda count method is used for fusion, which computes the sum ranks assigned by each classifier which are statistically independent. This fusion method is mathematically given as follows:

$$R_f = \sum_{x=1}^{M} R_{(x,y)} \tag{4}$$

No any training is required in this method. This method is affected by performance of individual classifier [18].

IV. RESULTS AND DISCUSSION

In this approach, the Adam optimization technique is used to improve recognition rate and generalization ability of network. The Adam optimization techniques are used because of its ability to converge faster than AdaGrand optimization technique which focuses on the infrequent feature parameter updating. The number of parameter in CNN design is increased so as to improve the generalization ability of network. The first of all the fast and efficient localization technique is used for localization of iris. This contributed in improving the overall accuracy of system. The results obtained are as follows:

A. Localization Accuracy

Initially pre-processing is done on iris databases to localize iris part. Fast and accurate iris localization model is used as per paper [13] . The localization accuracy of proposed model is calculated mathematically as given by formula

$$Accuracy\ Rate = \frac{(Correctly\ localised\ images)}{(Total\ Images)}\ X\ 10C \tag{5}$$

The localization accuracy found on iris databases is 99.82% and 99.87%. on CASIA-Iris-V3 and IITD data set respectively. This results shows that they have outperformed other state of art techniques.

B. CNN Architecture and Training Parameter Evaluation

While designing the CNN architecture, the *spoofnet*[19] architecture is taken in to account. Initially kernel size of **3X3** is used in both architectures.

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In second architecture initial 2 convolution layers use **3X3** kernel size. This is to preserve the spatial size of features at initial stages. The kernel size is increased in subsequent convolutional layer. The number of filter kept less at initial layers and then increased in subsequent layers. This is done to control model capacity. The padding of 1 is applied in first layer. In first architecture, padding is used at two places. The initial learning rate is set to 0.001. While training the number of epoch are set to 50. The training is stopped as soon as highest validation accuracy achieved on minimum validation error. After finishing the training of CNN, the validation data is used to calculate the accuracy of designed configuration. The output Validation error is fluctuating because of Adam optimization technique. Though the validation error rate is fluctuating but still it settles down to more global minimum than AdaGrand optimization technique. Adam optimization techniques have shown more generalization ability than AdaGrand optimization which helped further in using single architecture for both iris. The early stopping condition is used stop the training when desired accuracy is reached.. The overall training time is less than 50 minutes in each case. However it is observed that, the recognition rate is slightly dropped in case of IITD left iris database of image size 64X64 by 0.01%. The comparison of recognition rate with AdaGrand optimization technique is as shown Table II. The results obtained are compared with other existing system as shown in Table III. It is also noted that a single architecture provides comparably equal recognition rate which shows that better generalization ability.

TABLE IV. COMPARISION WITH ADAGRAD OPTIMIZATION TECHNIQUE

Size	Database	Method	Recognition Rate (%)	
			Left	Right
64X64	CASIA-V3	IirsConvNet[2]	99.88	99.94
		Proposed	100	100
	IITD	IirsConvNet[2]	99.92	99.82
		Proposed	99.91	99.91
128X128	CASIA-V3	IirsConvNet[2]	100	99.88
		Proposed	100	100
	IITD	IirsConvNet[2]	99.64	99.91
		Proposed	99.82	99.91

TABLE V. COMPARISION OF RECOGNITION RATE (%) OTHER EXISTING METHODS

Data set	Method	CRR(%)
IITD	Haar Wavelet [20]	98.45
	Log Gabor Filter[21]	97.19
	DCT[7]	95.17
	Texture+Scattering[5]	99.20
	Deep Convolutional Features[8]	99.4
	Proposed System	100
CASIA-V3	Texture Code[22]	100
	1D log polar Gabour Filter [23]	97.21
	Haar wavelet[20]	98.45
	Texture + Scattring[5]	99.20
	Proposed System	100

TABLE VI. COMPARISION OF RANK 1 IDETIFICATION RATE (%) USING BORDA COUNT METHOD

Data Set	Method	Identification Rate (%)
	Texture Code Matrix[22]	99.52
IITD	IrisConvNet[2]	100
	Proposed	100
CASIA-V3	Texture Code Matrix[22]	100
	IrisConvNet	100
	Proposed	100

C. Fusion Evaluation

Fusion evaluation Borda count method is employed to fuse the rank generated by classifier for each iris, and the ranks are assigned after the sample query is given and matching score are generated. Then these scores are arranged in descending order. This method has ability to exploit the capability of each classifier individually. The rank assigned to matching score of classifier is statistically independent of each other. This method is better than logistic regression classifier which needs training for finding weights of classifier. The Rank 1 identification rate is obtained after fusion techniques as shown in IV. The Rank 1 Identification rate obtained with Borda count method is 100% on both databases.The MATLAB code is written in 2018b. Simulation is done on Laptop Intel(R) core(TM) i5-7200U CPU with 4GB RAM.

V. CONCLUSION

The efficient pre-processing technique has increased the localization accuracy. The effect of this is contributed in overall system accuracy. The designed configuration of CNN used for both right and left eye is same and gives recognition rates comparably equal. The network training is done with Adam optimizer with other hyper-training parameter resulted in improved the recognition rate on individual data set. Compared with AdaGrand optimization, Adam optimizer has faster convergence rate in less computation and have shown improved accuracy on same databases, some are equal and only one slight reduced recognition rates on left eye of IITD of 64X64 sizes. A designed CNN architecture gives comparative same recognition rate on both right and left iris of same database. The final decision of identification is made with rank level fusion using Borda count method.The identification rate of overall system is found to be 100% for both databases.

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