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A Novel Approach for Face Recognition using Dual Cross Grouping Patterns and Neural Network

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ABSTRACT: In biometric identification, face recognition is one of most active research area. Different face recognition models proposed with the acceptable performance mostly under the supervised conditions. However, now days face recognition under uncontrolled conditions such as low resolution images, internet downloaded images, mobile and surveillance captured is gained significant researchers attention. The recognition of such face images is challenging research problem because of significant variations in face image quality, illumination, pose, occlusion and expressions. In this paper, a novel approach for Face Recognition using Dual Cross Grouping Patterns and Neural Network is proposed. This paper focuses on designing of face descriptor. After preprocessing of Gaussian operator DCP feature is computed both at component level and holistic level. The dimensionality reduction of face image is done by the Principal Component Analysis (PCA) and the recognition is performed by the Feed Forward Neural Network (FFNN). Experimental results are implemented on CAS-PEAL-R1 and LFW databases with variations in controlled and uncontrolled environment.

KEYWORDS:Biometrics; Face Recognition; Neural Network; Face representation; Pattern Classification

I. INTRODUCTION

Face recognition is an integral part of biometric technology which is used in Criminals identification, security system, passports verification, online banking, access control, information security, human computer interaction, driver licenses etc. Face recognition is a process of automatically identifying or verifying a person from a digital image or a video frame from a video source. The face recognition problem is challenging as it needs to account for all possible appearance variation caused by change in illumination, facial features, occlusions, etc. Face recognition system classify a face as either known or unknown comparing with stored face images.

A basic face recognition system may follow a Face Detection System whose function is to identify a face in a given image and ignore all the other background details. In the case of video, the detected faces may need to be tracked using a face tracking component. Face alignment aims at achieving more accurate localization and at normalizing faces thereby, whereas face detection provides coarse estimates of the location and scale of each detected face. Facial components, such as eyes, nose, and mouth and facial outline, are located; based on the location points, the input face image is normalized with respect to geometrical properties, such as sizeand pose, using geometrical transforms or morphing. The face is usually further normalized with respect to photometrical properties such illumination and gray scale. After the face image is extracted it is given as input to the Face Recognition System, which first extracts basic features of a face that distinguishes one from the other and then classifiers are used to match images with those stored in the database to identify a person. In face recognition applications, the original input data is usually of high dimension. Feature extraction is a process of transforming the input data to a reduced set of salient features. In face recognition the feature set is classified using different techniques namely Euclidean distance classifier, Bayesian classifier and neural network classifier. Using the data reduction, we reduce the dimension of the features but also important information is not destroyed [1].

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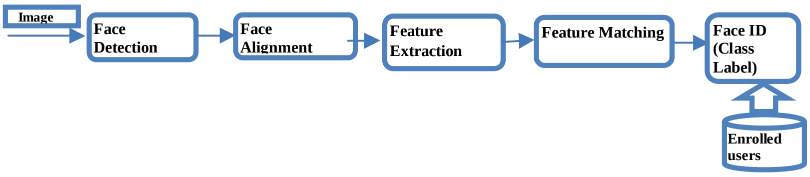

Fig. 1 Block diagram of Face Recognition System

II. RELATED WORK

Many literatures related to face recognition system which based on different approaches such as: Geometrical features; Eigenfaces; Template matching; Graph matching; and ANN approaches. The obtained recognition rates from these studies are different and based on: used approach; used database; and number of classes.

The various methods for face recognition can be grouped into four categories: knowledge-based methods, feature invariant approaches, template matching methods and appearance based methods. Knowledge-based methods are rule based methods. These methods try to capture human knowledge of faces, and translate them into a set of rules. The feature invariant approach finds some invariant features for face recognition. The idea is to overcome the limits of our instinctive knowledge of faces. The template matching methods compare input images with stored patterns of faces or features. The Appearance-based methods rely on techniques from statistical or probabilistic analysis and machine learning to find the relevant characteristics of face images. In generalappearance-based methods had been showing superior performance to the others [2][3].

Various face recognition techniques have its base from classical feature extraction method using Eigen faces [4], Fisher faces [5], Independent Component Analysis (ICA) [6]. Various popular classifiers include support vector machine(SVM), feed forward neural networks. All the above methods of feature extraction and classification involves the formation of row or column vector, as the images in a computer system are stored in the form of matrix i.e. 2D form, so it becomes easy to directly manipulate the image as in 2D form, it also prevents the information loss held in the classical methods of face recognition. Researchers proposed the new techniques that operates directly on the two dimensional data such that two-dimensional principal component analysis (2DPCA) and two dimensional linear discriminant analysis (2DLDA). These techniques are useful for reducing the computational complexity during the feature extraction [7].

The face representation was performed by using two categories. The First category is global approach or appearance-based, which uses holistic texture features and is applied to the face or specific region of it. The second category is feature-based or component-based, which uses the geometric relationship among the facial features like mouth, nose, and eyes. In face representation, good representations discriminate inter-personal differences while being robust to intra-personal variations. Two major categories of face representation methods dominate recent research, namely face image descriptor-based methods [8] and deep learning-based methods [9].

Based on design methodology, we can group existing face image descriptors into two groups: hand-crafted descriptors and learning-based descriptors. Most face image descriptors are hand-crafted, of which Local Binary Patterns (LBP) and Gabor wavelets are two representative methods. Ahonen et al. [10] showed that the texture descriptor LBP works by encoding the gray-value differences between each central pixel and its neighboring pixels into binary codes; the face image is then represented as the concatenated spatial histograms of the binary codes. Local Ternary Patterns (LTP) [11] was proposed to enhance the robustness of LBP to noises. Ding et. al. [12] proposed a Dual cross descriptor which gives good performance to variation in illumination, pose and expression. DCP encodes face image from multiple levels in to pattern.

III.FACE REPRESENTATION USING DUAL CROSS GROUPING PATTERNS

The design of a face image descriptor contains three main phases: image filtering, local sampling, and pattern encoding. In this paper, we focus on local sampling and pattern encoding, which are the core components of a face image descriptor.

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A. *Local Sampling:*

For face recognition, valuable face image data consists of two parts: the configuration of facial components and the shape of each facial component. After geometrical normalization of the face image, the central parts of some facial components, suchas the eyebrows, eyes, nose, and mouth, expand either horizontally or vertically, while their ends meet in almost diagonal directions.

For each central pixel O in the image, we evenly sample in the local region in the 0, $\pi/4$, $\pi/2$, $3\pi/4$, π, $5\pi/4$, $3\pi/2$, $7\pi/4$ directions, which gives main facial texture feature. Two pixels are sampled in each direction. The sampled points $\{A_0, A_1, A_2, A_3, A_4, A_5, A_6, A_7\}$ are uniformly spaced on an inner circle of radius R_{in}, whereas $\{B_0, B_1, B_2, B_3, B_4, B_5, B_6, B_7\}$ are evenly distributed on the exterior circle with radius R_{ex}. The process of local sampling of DCP is as shown in Fig. 2.

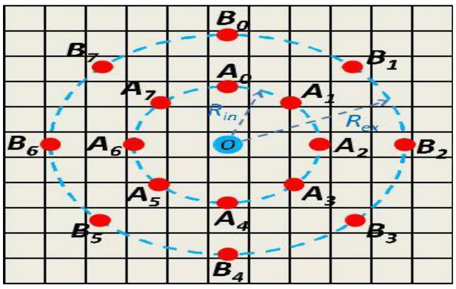

Fig 2. The process of local sampling of DCP pattern

B. *Pattern Encoding*

Sample points A_0 to A_7 on inner circle of radius R_{in} and Sample points B_0 to B_7 on outer circle of radius R_{ex} are encoded in two steps. Encoding of the sampled points is realized in two steps. First, textural information in each of the eight directions is independently encoded. Second, patterns in all eight directions are combined to form the DCP codes. To quantize the textural information in each sampling direction, we assign each a unique decimal number.

$$DCP_i = S(I_{A_i} - I_O) \times 2 + S(I_{B_i} - I_{A_i}), 0 \le i \le 7 \ldots(1)$$

$$S(x) = \begin{Bmatrix} 1, x \ge 0 \\ 0, x < 0 \end{Bmatrix} \ldots(2)$$

where I_O, I_{Ai} , and $I_{Bi}$are the gray value of points O, A_i, and B_i, respectively. Therefore, four patterns are defined to encode the second-order statistics in each direction and each of the four patterns denotes one type of textural structure. In real images, the pixels are spread so they are more independent. Therefore, the maximum joint Shannon entropy for each subset is reached when the distance between the sampled points is at its maximum. As a result, we define $\{DCP_0; DCP_2; DCP_4; DCP_6\}$ as the first subset and $\{DCP_1; DCP_3; DCP_5; DCP_7\}$ as the second sub-set. These two subsets make the shape of a cross, therefore the descriptor is termed Dual-Cross Patterns.

C. *DCP Face Image Descriptor*

The codes created by the two encoders at each pixel O are described by DCP1 and DCP2. The DCP descriptor for eachpixel O in an image is the concatenation of the two codes produced by the two cross encoders. After encoding each pixel in the face image using the dual-cross encoders, two code maps are produced that are respectively divided into a grid of non-overlapping regions. Histograms of DCP codes are calculated in each region and all histograms are concatenated to form the holistic face representation.

$$DCP\ 1 = \sum_{i=0}^{3} DCP_{2i} \times 4^i \ldots(3)$$

$$DCP\ 2 = \sum_{i=0}^{3} DCP_{2i+1} \times 4^i \ldots(4)$$

$$DCP = \left\{ \sum_{i=0}^{3} DCP_{2i} \times 4^i , \sum_{i=0}^{3} DCP_{2i+1} \times 4^i \right\} \ldots(5)$$

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IV. MULTI-DIRECTIONAL MULTI-LEVEL DUAL-CROSS PATTERNS

For normalization of face image MDML-DCP uses two operations such as similarity transformation and an affine transformation. The similarity transformation preserves the unique data of facial curves, facial components and their structure. The affine transformation decreases differences in intra-personal appearance created by pose difference. The outline of MDML-DCP Face representation system is as shown below in fig4.

Fig 3. Facial feature points detection on sample images

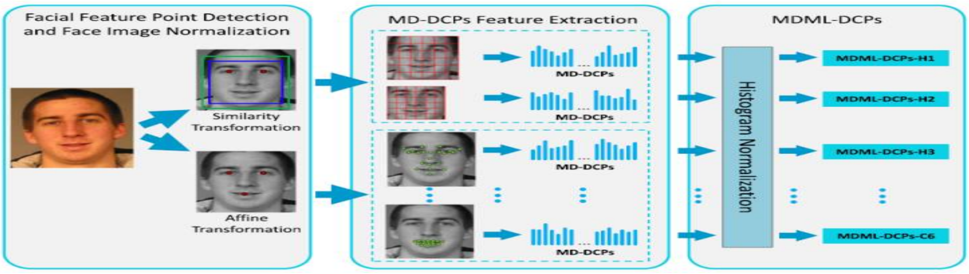

Fig 4. Structure of MDML-DCP Face representation system

MDML-DCPs combine both holistic-level and component-level features, which arecalculated on the normalized facial images by the two transformations. Holistic-level features store comprehensive information on both facial components and facial contour. However, it is also sensitive to changes in appearance of each component caused by occlusion, pose, and variations in expression. In contrast, component-level features focus on the description of a singlefacial component, and thus are independent of changes in appearance of the other components. The 49 facial feature points are detected by face alignment algorithm as shown in Fig. 3. MDML-DCP-H1 and MDML-DCP-H2 are extracted from similarity transformed image. MDML-DCP-H3, MDML-DCP-C1 to C6 are extracted from affine transformed image. The MDML-DCP face representation is collection of these normalized nine feature vectors. In this way the data generated by these two feature levels is complementary and appropriate fusion of the two helps robustness to interference.

V. NEURAL NETWORKS FOR CLASSIFICATION

Artificial Neural Network (ANN) is an interconnected group of artificial neurons that uses a mathematical method for processing the information. Neural networks have been widely applied in pattern recognition for the reason that neural networks based classifiers can incorporate both statistical and structural information and can be trained to achieve better performance than the simple minimum distance classifiers. The classification ability of neural network to a large extent depends on its architecture. Neural networks, with massive parallelism in its structure and high computation rates, provide a great alternative to other conventional classifiers and decision-making systems. Neural networks are powerful tools that can be trained to perform a complex and various functions in computer vision applications, such as pre-processing (boundary extraction, image restoration, image filtering), feature extraction (extract transformed domain features), associative memory (storing and retrieving information), and pattern recognition [13].

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Feed forward network provides a general frame work for representing nonlinear functional mapping between a set of input variables and set of output variables. The structure of the multilayer feed forward architecture is shown in Figure. The network consists of a number of layers and each layer output behaves as an input to the next layer. The hidden layers use tan sigmoid activation function and output layer uses linear activation function. The number of hidden layers and the number of neurons in each layer have to be recognized with repeated trials. In this type of networks connections to the neurons in the same or previous layers are not permitted [14].

A. *Training and simulation of Neural Networks*

The Learning Process There are basically two major categories of learning methods used for neural networks Supervise learning, unsupervised learning method. Supervised learning which work as an external teacher or guide, so that each output unit is expressed to perform what should be desired response to the respected input signals. Transfer Function The whole behaviour of our Neural Network totally depends on both the weights and the input-output function that is specified in the all units. There are mainly three categories of Transfer Functions: Linear (or ramp), Threshold, Sigmoid. When a new image from the test set is considered for recognition, the image is mapped to the Eigenspace or Fisherspace. Hence, the image is assigned to a feature vector.Each feature vector is served to its corresponding neural network and the network outputs are compared [15].

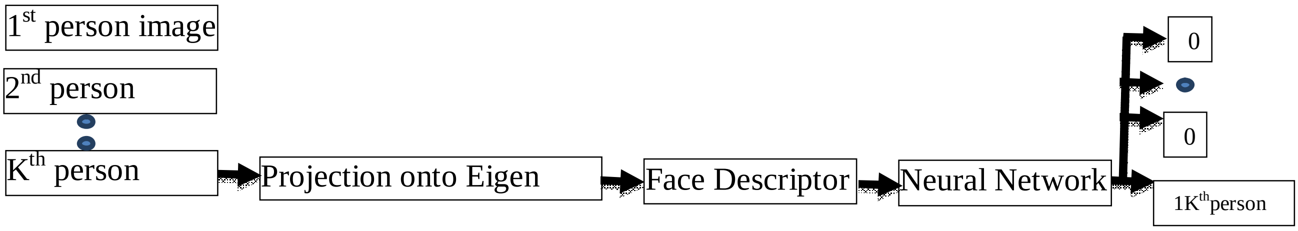

Fig. 5 Training and simulation of Neural Networks

VI. EXPERIMENTS AND RESULTS

Experiments are performed on two publicly available large scale face databases: CAS-PEAL-R1 and LFW.
CAS-PEAL-R1 [16] database includes one training set and nine probe set. Each of the nine probe sets is restricted to one type of variation. The PE, PA, PL, PT, PB and PS probe sets correspond to variations in expression, accessory, lighting, time, background, and distance of frontal faces respectively.
The Labelled Faces in the Wild (LFW) database [17] consists of realistic and naturally occurring face images captured in uncontrolled environments and downloaded from the internet. The LFW database includes 13,233 images of 5,749 subjects. Face images in LFW contain large variations in pose, illumination, and expression, and may be arbitrarily occluded.

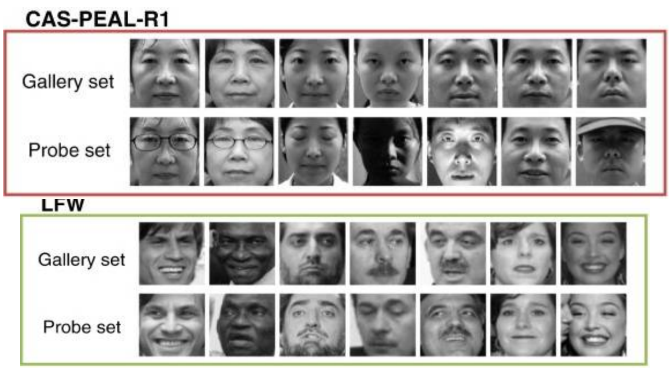

Fig. 6 Sample images from CAS-PEAL-R1 and LFW face database

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Performance Measures:

- Sensitivity (true positive rate): measures the proportion of positives that are correctly identified
  Sen = (TP /(TP+FN))*100
- Specificity (true negative rate): measures the proportion of negatives that are correctly identified
  Spe = (TN /(TN+FP))*100
- Accuracy : Auc = ((TP+TN)/(TP+FN+FP+TN))*100

		Prediction		
		Positive	Negative	
Ground truth	Positive	**True positive (TP)**	**False negative (FN)**	**True positive rate** $\frac{\#TP}{\#TP + \#FN}$
	Negative	**False positive (FP)**	**True negative (TN)**	**False positive rate** $\frac{\#FP}{\#FP + \#TN}$

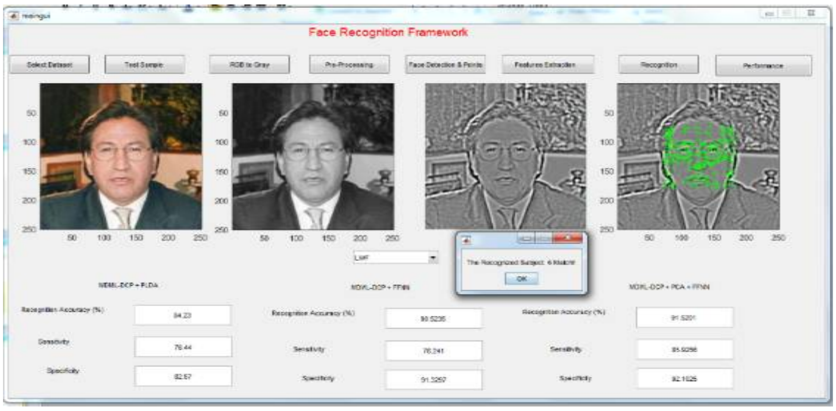

Fig. 6 Proposed frameworks for face recognition

Identification results for each descriptor on nine probe set of CAS-PEAL-R1and LFW database are shown in Table Iand Table II And graphical representations is shown in Fig.7.

TABLE I

Rank-1 Identification Rates for Different Face Image Descriptors on the Nine Probe Sets of CAS-PEAL-R1

Methods	PE	PA	PT	PB	PS	PL	PU	PM	PD
LBP	94.27	91.82	100.0	99.46	99.64	46.90	60.32	83.66	44.60
LTP	94.39	91.77	100.0	99.46	99.64	47.17	61.32	84.46	44.68
DCP1	95.99	92.60	100.0	98.73	99.27	46.37	60.68	85.74	48.14
DCP2	95.54	91.90	100.0	98.92	99.64	43.91	60.64	83.08	43.62
MDMLDCP	96.11	92.82	100.0	99.10	99.64	50.25	65.39	87.44	51.30

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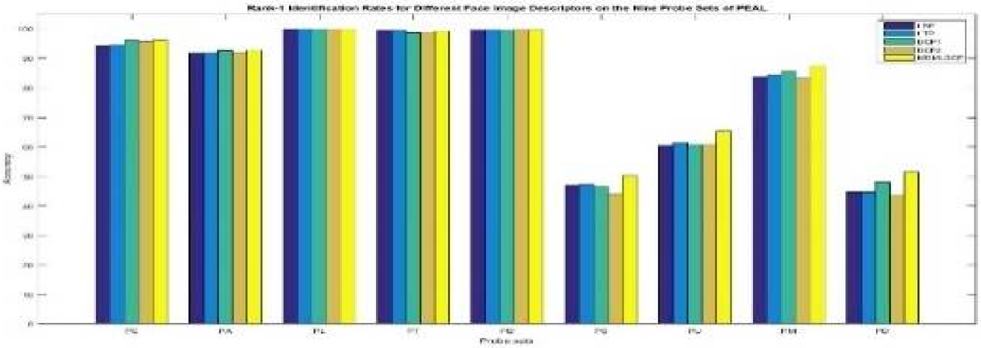

Fig. 7.Graphical representations of various descriptors on CAS-PEAL

TABLE III

Rank-1 Identification Rates on LFW database

Method	Accuracy
LBP	72.43
LTP	72.65
DCP1	74.50
DCP2	73.28
MDMLDCP	84.00

Comparison of results are shown in Table 3.

TABLE IIIII

Performance comparison between MsLBP and DCP on face datasets

Databse	Method	
	MsLBP	DCP
CAS-PEAL(FRONTAL)	89.01	89.65
CAS-PEAL(POSE)	63.93	68.08
LFW	72.88	75.00

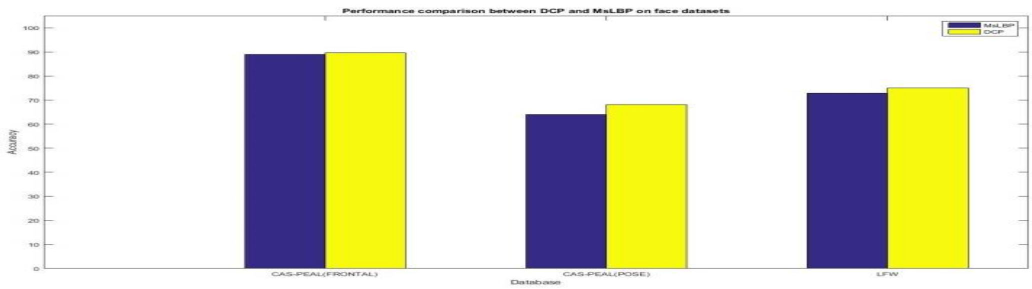

TABLE IVV

Performance Comparison on both databases

Method	Accuracy	
	CAS-PEAL	LFW
MDML-DCPs-PLDA	71.48	84.23
MDML-DCPs-WPCA	73.70	90.52
MDML-DCPs-PCA+FFNN	74.18	91.52

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VII. CONCLUSION AND FUTURE WORK

Face recognition is one of biometric methods, to identify given face image using main features of face. In this paper, a neural based algorithm is presented, to detect frontal views of faces. Feature extraction is done by using dual cross pattern descriptor. The dimensionality of face image is reduced by the Principal Component Analysis (PCA) and the recognition is done by the Feed Forward Neural Network (FFNN). The proposed method gives systematic approach to design. It combines the benefits of both single layer feed forward neural network and multilayer feed forward neural network. Here face images are taken from CAS-PEAL and LFW facedatabases. Feed forward Neural Network based Face recognition is robust and it gives improved performance than existing approaches.Future work can be done by using advanced machine learning techniques for optimal feature selection and advanced feature matching strategies to improve the method.

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