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A discrete region inferred differential evolution feature selection architecture for human face recognition

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***Abstract*---**Face Recognition has received a lot of attention in wide variety of the security application employing face based biometric authentication due to its non intrusive data acquisition. Especially artificial intelligence play important role in face recognition**.** Numerous researches have been carried out using machine learning technique in order to accuracy of the recognition. In this paper, a novel technique titled as Discrete Differential Evolution (DDE) architecture has been proposed. The proposed architecture will employed after set of the primary image processing steps such as preprocessing, feature extraction and feature selection. Initially preprocessing of the images is performed with image normalization technique and image enhancement technique. Preprocessed image will explored to Linear Discriminant Analysis technique to extract the features of the image. Extracted features will contain some redundant and irrelevant information of the images, it has to eliminate and optimal feature has to be selected to the recognition task. Discrete Region Inferred Differential Evolution architecture is employed to feature selection. Extracted features will be consider as search space, objective function of the DDE generates the optimal features solutions with respect to fitness criteria. Finally recognition task is performed with optimal features using support vector machine. . Experimental is carried out with Yale dataset, the dataset is categorized into training and testing set. Testing data utilized for 5 fold validation of the proposed architecture. The performance analysis of the proposed architecture provides high accuracy and less computation cost on comparing against state of art approaches

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***Keywords*---**face recognition, linear discriminant analysis, support vector machine, differential evolution, biometric authentication.

Introduction

Face recognition is becoming popular in security based applications in situation like covid -19 pandemic due to non intrusive data acquisitions [1]**.** However, the image acquisitions sensor will faces several challenges by shades and changes in illumination effects. Processing of those artifacts will lead to degradation of recognition accuracy [2]. In order to tackle those challenges, preprocessing of the image is carried out using noise removal and image normalization techniques. Many feature based methods has been developed to face recognition such as Discrete Wavelet Transform [3] and Discrete Cosine Transform [4] but those techniques fails to produce linear features which further results to reduced recognition accuracy. In addition, those techniques process with Discriminant and redundant features. This leads to undesirable results with high computational cost. Taking aforementioned challenges of feature learning methods into consideration, a new feature engineering method for effective recognition has been proposed in this paper.

In order to enhance the recognition rate of face recognition accuracy, a new discrete differential evolution technique has been proposed as feature learning architecture in this paper. Feature learning is employed with feature extraction and feature selection mechanisms. Initially feature extraction techniques such as linear Discriminant analysis [5] have been used to extract the characteristics features of the image. Extracted features undergo feature selection through discrete differential evolution. Discrete differential evolution technique generates the optimal set of the feature on basis of its objective function and fitness criteria. The optimal feature classified using support vector machine[6] for face recognition. Discrete Differential Evolution produces less no of features for recognition.

The remaining paper is sectioned into following; Section 2 presents the related work of the face recognition models. In section 3, proposed face recognition model is described in detail with objective and fitness constraints. The Experimental analysis is carried out in the section 4 against various performance measures. Finally, the section 5 concludes the work.

Related works

In this section, existing face recognition models has been analyzed on various aspects of feature extraction and selection to produce high recognition accuracy. Especially Discrete Wavelet transform and Discrete Cosine transform has been discussed in detail, its detailed process description is as follows

Face Recognition using Discrete Wavelet Transform

In this model, face features are extracted using wavelet bands containing the approximation components with most discriminative texture feature representation. The extracted features are analyzed for discriminative ability using the image histograms on various face image orientations [7]. Finally matching score determine the effective of recognition on extracted features using appearance based techniques.

Face Recognition using Discriminative Cosine Transform

In this model, feature is extracted using Cosine transform[8] is processed in form matrix containing feature vectors. Those feature vectors has been processed with frequency estimation to discriminate features. It further enhances the discriminative ability of the global and local features through multi-directional pixel difference vectors for each pixel and its neighboring pixel. Finally face recognition is carried using SVM classifier[8] with the less no of optimal features using meta-heuristic techniques.

Proposed model

The Proposed model for face recognition composed of following feature engineering modules, such as feature extraction, Feature selection and Feature classification. The feature classification performed on the optimal set of features using the meta-heuristics approaches[9] on texture based features extracted. As initial step, face image acquired will undergo pre-processing and feature extraction.

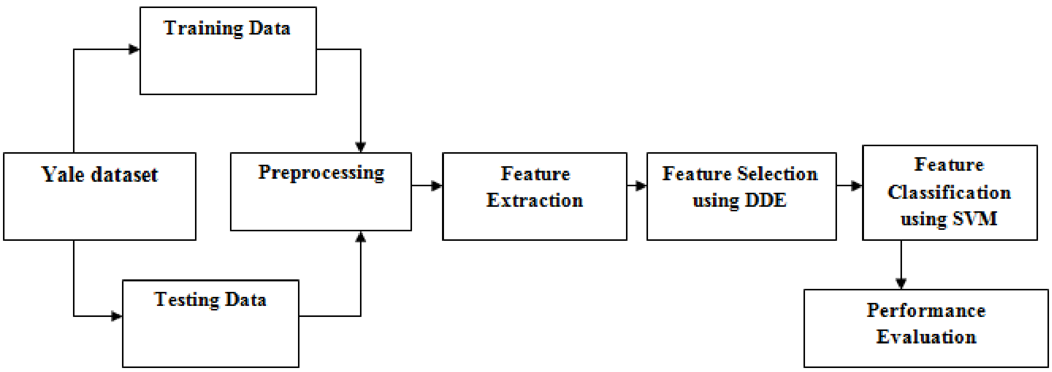

Figure 1: Architecture of the Proposed Face Recognition Architecture

The overall architecture of the proposed face recognition architecture using differential evolution technique is illustrated in Figure 1. Process of the face recognition is carried out on training data and performance is evaluated with testing data to extract the relevant optimal features through feature classification using modified support vector machine.

Pre-processing of the Training data

Face images resulted to shadow and illumination effects. Those effects will eliminated using preprocessing of the image using image normalization and noise removal techniques named as contrast limited adaptive histogram equalization [10]. It computes histogram of the each pixel and calculates the Cumulative Distribution Functions[11] for mapping the effecting pixels in the image. Finally it results with high quality of image artifacts for feature learning.

Feature Extraction

The feature extraction phase aims to extract the characteristics features of face images through following dimensionality reduction technique such as

Linear Discriminant analysis

Linear Discriminant analysis is used to extract the relevant characteristic features from the image. In this part, Image is transformed into Scatter matrix [12]. Scatter Matrix generates the feature vector using fisher criterion function. Initial assumption is that the good feature of the vector should have least variation or distance value between the feature instances of the vector which considered as intra vector variation.LDA considered as efficient matrix transformation vector**.** Feature vector from scatter matrix is of N x N, In this matrix the mean vector is computed as .

Mean Vector for first element matrix

$$Mv = \frac{1}{n} \sum_{x \varepsilon C}^{n} x, n_i$$

Scatter Matrix with all elements is

$$S_w = \sum_{x \varepsilon C}^{n} n\, Mv$$

Further ratio weight of the matrix elements gets maximized when eigenvectors of S_w produces the column vector of the relevant instance is as

$$R = [Mv\, R_1, Mv\, R_2 \ldots\ldots\ldots\, Mv\, R_{c-1}]$$

Where W_i are the eigenvectors of Sw

Linear Discriminant analysis has computed on basis fishermen pair wise similarities criteria of the characteristics features extracted on the variance of the matrix elements from the two or more vectors.

Feature Selection

Feature Selection is a process to compute the less no of optimal features to increase the classification accuracy and to reduce the computation cost by eliminating the redundant and irrelevant features. In this work, a discrete differential Evolution model has been employed to generate the less no of optimal features for face recognition. In this category is collection of feature or its values to represent individual.

Discrete Differential Evolution Model (DDE)

Discrete Differential Evolution is a meta-heuristic candidate search algorithm composed of feature handling step. Initially feature extracted from the LDA is modeled as population. Those populations will undergo set of process named as Mutation, Recombination and Selection. In mutation process, distinct feature will selected from the vector.

In this part, the search space of the problem by DE and the range of parameters it can select the optimal features has been defined through feature vector. Then, the optimization algorithm[13] to choose the best configuration based on the fitness function in terms of recognition rate has been computed. From there, the optimization algorithm acts with its intrinsic mechanisms to choose the best relationship between the features through their respective parameters' values. Hence, the output features are those provided by the DE indicate the ability to explore distinct features present in databases.

Table 1: Parameter Setting for Feature Selection using Discrete Region Inferred Differential Evolution

Parameters	Size
Population Size	50
Scaling Factor	0.85
Cross Over	0.7
Mutation	0.5
Max_iteration	100

Table 1 shows the training parameters setting used for feature selection of DRIDE. DRIDE generates the optimal feature from the particular feature vector on computation of mutation, cross over and fitness computation on basis of objective function of the meta-heuristics model. In recombination process, highly weighted feature in the vector will selected. Finally selection process selects the top ranked features from recombination process.

Objective Function of DRIDE is given as $\gamma ki(x_k) = \sum_{m=k}^{n-1} abs(v_i^j(x_k) - v_i^j(x_{m+1}))$

Where $v_i^j(x_k)$ denotes the value of feature in the selection vector and n is the number of the features in the final selection vector. Important objective of DRIDE technique is to reduce γki while increasing abs. This can be achieved by maximizing the ratio $| v_i^j | / | v_i^i |$. Further ratio weight gets maximized when eigenvectors of abs form the column vector of the projection matrix

$W= [W_1, W_2 \ldots\ldots\ldots\ldots W_{c-1}]$

Where W_i are the eigenvectors of the abs_i and abs_j corresponding to the set of decreasing eigenvalues λ_i.

Feature Classification using Support Vector Machine

The optimal feature obtained on feature selection techniques is processed in support vector machine to classify the feature. It classifies the features on construction of the hyperplane for the features. It is a non parametric method [14]. The method is considered to be the instance based as it recognizes the instance into the class. Class labels are predicted by the distance weighting estimation to train feature samples as classes and recognizes the class label for the sample.

Let X is the optimal feature vector and T_{ij} is the distance measure between the weighted features. The distance estimation is carried out using Euclidean distance can be represented as

$$D_i(y)=||y-T_{ij}||^2$$

Where T_{ij} is classes recognized for optimal feature vector.

Support vector machine classifies the optimal features into the various classes on basis of the distance computation between the features effectively. Feature vector classification yields between recognition accuracy. It seems to be an appropriate choice to compensate these variations to a certain level.

Experimental Analysis

In this work, experimental analysis is carried out in Yale dataset for face recognition using discrete region inferred feature selected on appearance based features. The experimental results have been computed and its performance has been evaluated on various test testing through 5 fold cross validation is described in following sections.

Experimental Environment and Dataset Description

The experiment was carried out using MATLAB R2018 on window 7 Intel Core i7 CPU with operating frequency of 2.53G Hz. The dataset used in this work contains the face image of various subjects containing 1280x960 resolutions.

Dataset Description –Yale dataset

Yale Dataset[15] consists of 165 facial images of 15 persons, which has 11 different images including expressions of each person. In that, 120 face images with 8 different images of each person treated as Train dataset. Remaining 45 images are treated as test images, they are considered as out of the database images to measure FAR.

Training phase

On Training of the face recognition architecture with 80% of the sample images, face patterns are extracted using Linear Discriminant Analysis. Those extracted feature has been employed to Feature selection and classification process using

Discrete Differential Evolution and Support Vector Machine. . The state- of-the-art methods are compared by dividing them into non- training-based and training-based methods

In this section, we present experiments to show the effectiveness of the proposed method feature sets extracted from LDA model. In LDA model, the adjacent pixels in an image are usually correlated. The information redundancy can be reduced by down sampling the feature images on discrete region. In our experiments, the feature images are down sampled LDA by factor of n using the region inferred histograms.

Testing Phase

Testing of the face recognition architecture is carried out with 20% of the sample images for 5 fold validation on exchanging of images. Each fold validation undergoes the feature extraction, selection and classification process. Face patterns extracted using single dimensional feature vectors through Linear Discriminant Analysis. In our experiments, the feature images are down sampled LDA by factor of n. In this n can be any number between 1 to 5.

Table 2: Performance Comparison of proposed model using LDA-DRIDE

Threshold	0.1	0.2	0.01	0.03	0.05
Accuracy	99.28	98.97	98.56	98.24	98.01
FRR	0.2	0.2	0.2	0.3	0.3
FAR	0.3	0.3	0.3	0.3	0.3
Precision	99.78	99.67	99.51	99.39	99.24
Recall	100	100	100	100	100

N - Dimensional feature vector is extracted from each point and the final feature vector is constructed by LDA. . However Feature vector improves the recognition which further undergoes feature selection using DRIDE. Initially parameter setting for the feature selection model using DRIDE and has been tabulated.

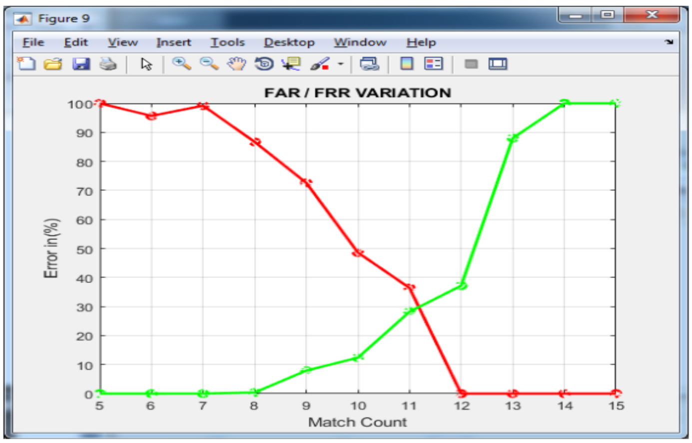

Figure 2: Face Recognition Error analysis

The performance of the recognition model is computed on basis of accuracy as represented in the figure 2. In this mutation factor lies between (0,2) as it controls the rate of the population evolves in the vector.

Table 3 provides the performance of face recognition technique on various performances metric such as Accuracy, Recall and Precision along False acceptance rate and false rejection rate to the classification techniques as feature extraction technique was responsible for the recognition rates of the biometric images.

Table 3: Performance comparison of classifier for finger vein recognition on optimal feature

Classifiers	Accuracy (%)	Recall (%)	Precision (%)	FRR (%)	FAR (%)
SVM	98	93.6	100	6.25	1.54
K NN	94	91.2	100	0	0

The SVM classifier is applied to feature selected using DDE to recognize the face images. Feature generated through DDE, produce the improved classification accuracy on increase of the samples, reduced computation time on training and testing. In this different strategies can give the same approximate recognition rates, but with different processing times as an optimization criterion to face recognition.

Conclusion

We designed and implemented new face recognition architecture using discrete differential evolution. In this work, Linear Discriminant Analysis has been employed to produce the characteristic features. Moreover those features are processed further in the DRIDE which is considered as population based Meta heuristics optimization technique to generate optimal set of feature for effective feature classification. Finally Support Vector Machine based classifier has been applied to classify the optimal feature on the training and testing set of the dataset. . From the experiments results, it is inferred that proposed DDE are significantly produces the improved recognition accuracy of 99.89%

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