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HUMAN EYE DETECTION IN WAVELET DOMAIN USING DISCRIMINANT ANALYSIS

[1] **Mr. T. YUVARAJ,**
[1] Research Scholar,
[1] Department of Computer. Science,
[1] Govt Arts College (Autonomous),
[1] Salem – 636007.

[2] **Mrs. D. CHITRA, MCA, M.Phil,**
[2] Assistant Professor,
[2] PG & Research Dept of Computer. Science,
[2] Govt Arts College (Autonomous),
[2] Salem – 636007.

Abstract: -

In this paper, we have to shows overcomes the problems on the fisher linear discriminant in such as performance in two class problems.Using some techniques on the clustering method to implement the clustering –based discriminant(CDA) models to obtain the problem on this system. Parametric and non – parametric both clusters are handled in this system from face databases are handled feasibly widely on the CDA models. Using efficient classification technique such as KNN classifier to detect the person to matched input eye image. The observations can be projected onto the subspace, resulting in a set of variables that captures most of the clustering information available. The use of generalized hyperbolic mixtures gives a robust framework capable of dealing with skewed clusters. Although dimension reductionis increasingly in demand across many application areas, the authors are most familiarwith biological applications and so two of the three real data examples are within thatsphere. Simulated data are also used for illustration.

Keyword: - Cluster, Image, CDA, databases, Parametric.

1. INTRODUCTION

Fisher linear discriminant is the popular tool for feature extraction and classification methods.Due to some problems on the classes of the models from occurs the problems on the operation of the FLD process.All classes are divided to many clusters using three levels of he models and the to accurate efficient eye detection method.This clustering based analysis is the means to using many efficinet clustering and classification techniques. Many dimension reduction methods summarize the information available through a reduced subset of the original variables; however, they provide little information on the potential structure of the data at hand. The method proposed herein addresses this issue by revealing the underlying data clusters. At the same time, using heavy-tailed distributions, such as the generalized hyperbolic, to model data can be advantageous because they assign correct weights to extreme events. The goal is to estimate a subspace that captures most of the clustering structure contained in the data. At the core of the method lies the sliced inverse regression (SIR) work of Li (1991, 2000), which reduces data dimensionality by considering the variation in both group means and co variances. The members of the sub-space arise through linear combinations of the original data, and are ordered by importance via their associated eigen values. The original observations in the data can be projected on to the subspace, resulting in a set of variables that captures most of the clustering information available. NN methods for face recognition by using PCA and LDA method. The patterns are divided into several small-scale subnets based on FCM. Due to the negation ability of NN and parallel NNs, some candidates are excluded. The similarities between the remaining candidates and the test patterns are calculated. It judged the candidate with the greatest similarity to be the final answer when the similarity value was above the threshold value. Otherwise, it was judged to be nonregistered. This project was compared with LDA and PCA method, and it was analyzed .The result of this analysis is, the PCA method is better than the LDA Used feature vector representation by using independent component analysis (ICA) for enhancing the performance by reducing the dimensions. They find more accurate results in terms of accuracy. Shobeirinejad et al. used Feature extraction using Interlaced Derivative Pattern (IDP). They improved performance by increasing system speed and reducing error. Their proposed detect error and increase system speed. Their main focused on reduced computational complexity compared with Local Derivative Pattern (LDP). Yuchun Fang et al. used Feature extraction using local Binary Pattern (LBP) and Principal Component Analysis (PCA). They reduce the redundant information of high density LPB features. Their proposed method Traditional LBP features are improved results in a classification accuracy and fast process Our contributions are as follows. First, we propose a novel criterion for dimensionality reduction, called Discriminant Tensor Criterion, which maximizes the inter-class scatters and at the same time minimizes the intra-class scatters both measured in the tensor based metric. Different from the traditional sub-space learning criterion which derives only one subspace, in our approach multiple interrelated subspaces are obtained through the optimization of the criterion where the number of the subspaces is determined by the order of the feature tensor used. The data set was randomly partitioned into gallery and probe sets; and two samples per person was used for training. We extracted 40 Gabor features with five different scales and eight different directions in the down-sampled positions and each image is encoded as a 3rd order tensor of size 16*16*40. Table 2 shows the detailed face recognition accuracies. The results clearly demonstrate that DATER/3-3 is superior to all other algorithms. Moreover, it shows that the Gabor feature can help improve the face recognition accuracy in both Eigen face and Fisher face.

2. LITERATURE REVIEW

Title: Improved Fa cial-Feature Detection for AVSP via Unsupervised Clustering and Discriminant Analysis.

Author Name: Simon Lucey, Sridha Sridhara n, Vinod Chandran An integral part of any audio-visual speech processing (AVSP) system is the front-end visual system that dete cts f acial features(e.g ., eyes and mouth) pertinent to the task of visual speech processing . The ability of this front-end system to n ot only locate,but also give a confidence measure that the facial feature is present in the image, directly affects the ability of any subsequent post processing task such as speech or speaker recognition. With these issues in mind, this paper presents a framewor k for a facial-feature detection system suitable for use in an AVSP system, but whose basic framework is useful for any application requiring frontal facial-feature detection. A novel approach for facial-feature detection is presented, based on an appearance paradigm. This approach , based on intraclass unsupervised clustering and discriminant analysis, displays improved detection performance over conventional techniques.

Title : Kernel Fisher Analysis Method for Face Recognition.

Author Name : Amruta S. Moon, Yogdhar Pandey, Megha Kamble (2012) This paper deals with the correspondence presents Color and Frequency Features based face recognition. The CFF method, which applies an Enhanced Fisher Model (EFM), extracts the complementary frequency features in a new hybrid color space for improving face recognition performance. A color image in the RGB color space consists of the red, green, and blue component images.

The new color space, the RIQ color space, which combines the R component image of the RGB color space and the chromatic components I and Q of the YIQ color space, displays prominent capability for improving face recognition performance due to the complementary characteristics of its component images.

Title:red-eyes removal through cluster basedlinear discriminant analysis

Author Name:S. Battiato, G. M. Farinella ,M. Guarnera, G. Messina, D. Rav` A set of linear discriminant classi fiers is then learned on the clusteredpatches space, and hence employed to distinguish between eyes andnon-eyes patches. The proposed cluster-based Linear DiscriminantAnalysis is used to deal with the multi-modally nature of the inputspace. The third step of the pipeline is devoted to artifacts correc-tion through de-saturation and brightness reduction. Experimentalresults on a large dataset of images demonstrate the effectiveness ofthe pro- posed pipeline that outperforms other existing solutions interms of hit rates maximization, false positives reduction and ad-hocquality measure.

Title: Push-Pull Marginal Discriminant Analysis for Feature Extraction

Author Name: Zhenghong Gu, Jian Yang, Lei Zhang Marginal information is of great importance for classification. This paper presents a new nonparametric linear discriminant analysis method named Push-Pull marginal discriminant analysis (PPMDA), which takes full advantage of marginal information. For two-class cases, the idea of this method is to determine projecteddirections such that the marginal samples of one class are pushed away from the between-class marginal samples as far as possible and simultaneously pulled to the within-class samples as close as possible.

This idea can be extended for multi-class cases and give rise to the PPMDA algorithm for feature extraction of multi-class problems. To compared to the FLDA method, an additional computational cost of PPMDA is required for the nearest neighbor search.

The naive (linear) search of the k neighbors of one point within iC has a running time of O(kNiD), where Ni is the number of samples in I C and D is of dimension of the pattern vectors.

So the computational complexity for nearest neighbor search in PPMDA is O(kN2D), where is N is total number of training samples, ==c I I N N1. The naive search algorithm only suits for small sample size cases.

3. PROPOSED SYSTEM STRUCTURE

We have to proposes the overcome technique to for two class problems on detecting the eye on faces using some models of the cluster based discriminant algorithms (CDA) in the process of classification and feature extraction.In this process we have process the obtain the satisfactory performances on the received values of this processes.We have to implement the very efficient clustering techniques such as k-means Clustering in between many number of clusters on the knn classification system.To measure the difference between the levels such as between-cluster matrix at local based and between – cluster matrix at global based from to computes the performance of the whole process. For each intermediate concern, the first variantplaced the points of data set which assurances thehighest minimization in errors of clusteringwhen initializing the new cluster in order to add this point and perform kernel means just onetime from the initialization. Nevertheless, the other variant is positioned in the set of data, byplacing a model of convex mixture. For everyintermediate problem of mixture then tries just examples as an initialization possible for thecluster which are new rather than of the complete set of data. The study focused in the comparison of the different methods interms of the similarity of the results, with the aim to find similar behavior. Another focus was onthe flexibility of the algorithms with respect to the records, as well as the sparseness of the dataand the dimensionalities have a major impact on theproblem. In conclusion, it has been achievedwith a combination of recommender systems, hierarchical methods, and Affinity Propagationgood results. Kernel-based algorithms were sensitive with respect to changes in the output dataset. This optimization objective is often called thek-means clustering objective. (See Definition 1 for a formal discussion of thek-means objective.) The simplicityof the objective, as well as the good behavior of the associated algorithm (Lloyd's method),have madek-means enormously popular in applications. In recent years, the high dimensionality of the modern massive datasets has provided a

considerablechallenge tok-means clustering approaches.
First, the curse of dimensionality can make algorithmsfork-means clustering very slow, and, second, the existence of many irrelevant features may notallow the identification of the relevant underlying structure in the data.
ractitioners addressed such obstacles by introducing feature selection and feature extractiontechniques.

3.1. Modules of the Proposed System

In existing we have to extract the features and classify the eye images using the Fisher Linear Discriminant (FLD) process with few levels of models.
In this process recognizes the patterns of the eyes to using some numeric fields such matrices process the classification and feature extraction.Thos method is performed to separability from process the optimal linear projection method to reduce the feature dimensionality.
The Proposed system consists of following modules. Such as,

- Preprocessing.
- Wavelet Transforming.
- Feature extraction.
- Classification.

The preprocess is one of the process which helps to prepare the images for our proposed work.
In preprocess the Input face to be Pre-processed such as gray - Scaled, filtered and then enhanced for the feature extraction process.
Then the feature values are extracted from the input Face for extract the corresponding features in the Face of Input image.
Wavelet transformation is the very useful domain transformation method in time – to – frequency transformation on the input preprocessed images.
In this transformation time should allow on transaction to change he values, but not in shape.
This transformation should d be obtained resolution of different probabilities such as time frequency and scaling factor in the images.This module we have to transform our normalized input images effectively.

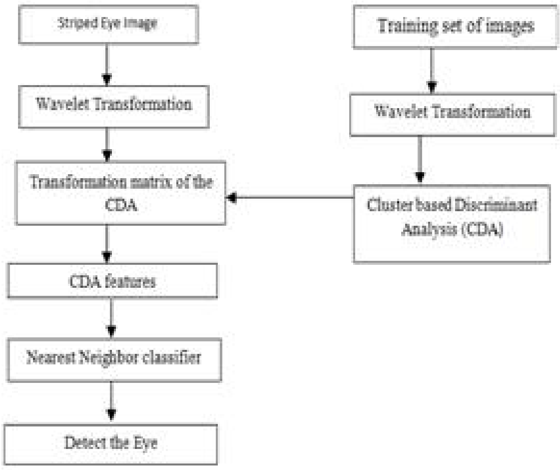

Figure 1: Structure of Proposed System

The wavelet transform decomposes thesignal into different scales with differentlevels of resolution by dilating a single prototype function, the mother wavelet.Furthermore, a mother wavelet has to satisfy that it has a zero net area, which suggest thatthe transformation kernel of the wavelettransform is a compactly support function(localized in time), thereby offering the potential to capture the PD spikes whichnormally occur in a short period of time
The feature extraction will help to identification process by reduce the complexity of the classifier work.The feature extraction convert the image form matrix to vector by extract the pixel information of the image.In our proposed we use CDA feature extraction process, by Local binary pattern (LBP).This is the important module in this process to compare those selected set is compared from to the existing Datasets.
Classification is used to classify the feature to identify the person during the identification.In our process we have to done the knn classification for extracted features from the input images.This step using to extract features from the given images, and then perform classified to the all images each by each in the database.This technique is very useful for identify desired output from the existing dataset in this process. This is the final process for to detect the eye of the perfect person in the existing dataset The clustering baseddiscriminant analysis (CDA), and show its feasibility for the facial expression recognition problems. CDA is modified from LDA methods. Unlike PCA, which is designed for representation, CDA method extracts features with discriminant power;unlike LDA, which separates the

whole classmeans, CDA seeks to separate clusters of differentclasses. Experimental results show that CDA generates better results than LDA in terms of the classification accuracy.

4. SYSTEM IMPLEMENTATION

We have to implement the very efficient clustering techniques such as k-means Clustering in between many number of clusters on the knn classification system.To measure the difference between the levels such as between-cluster matrix at local based and between – cluster matrix at global based from to computes the performance of the whole process.

Figure 2: Image Selection

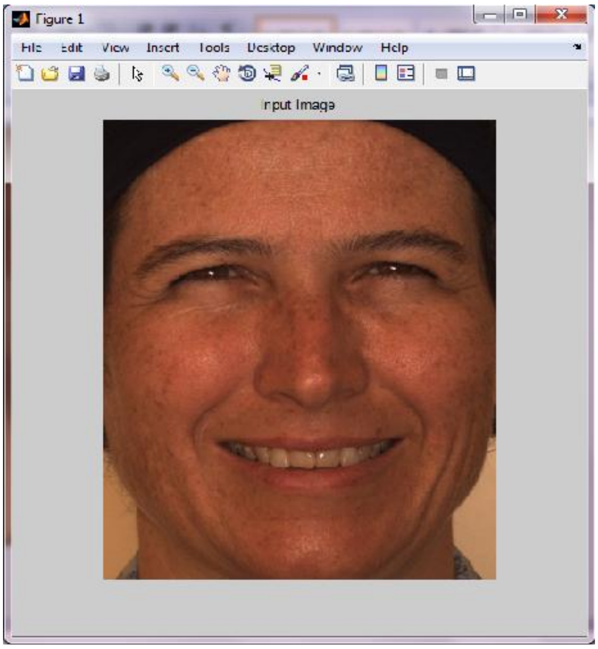

Figure 3: Actual Image

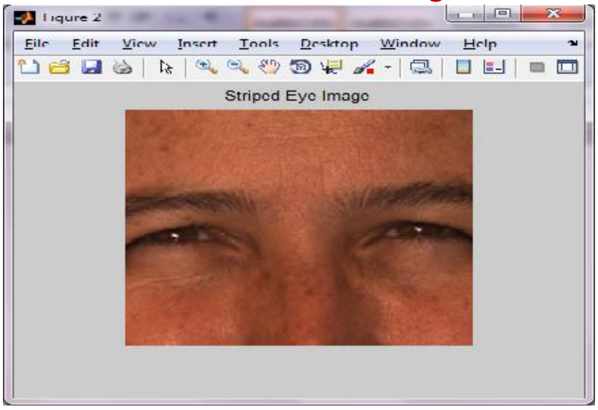

Figure 4: Striped Eye image

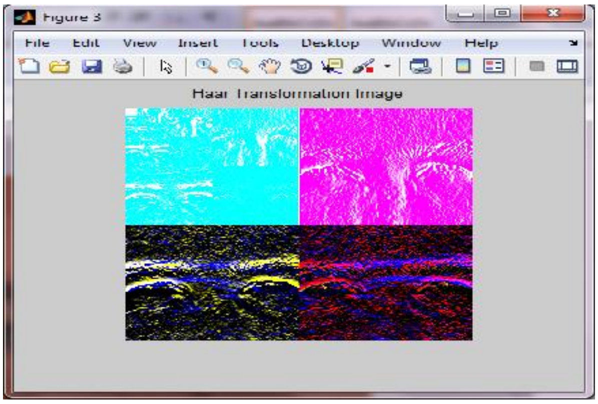

Figure 5: Haar Transformed Image

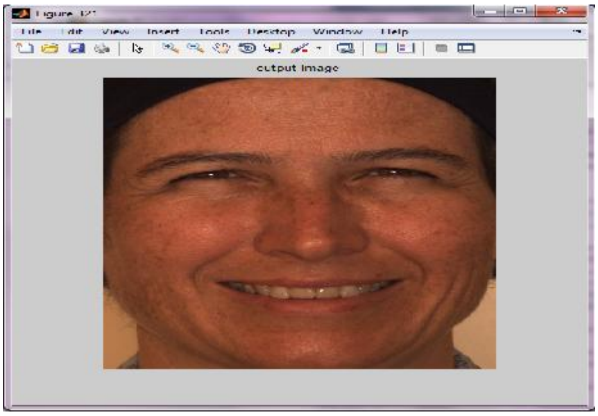

Figure 6: Output Image

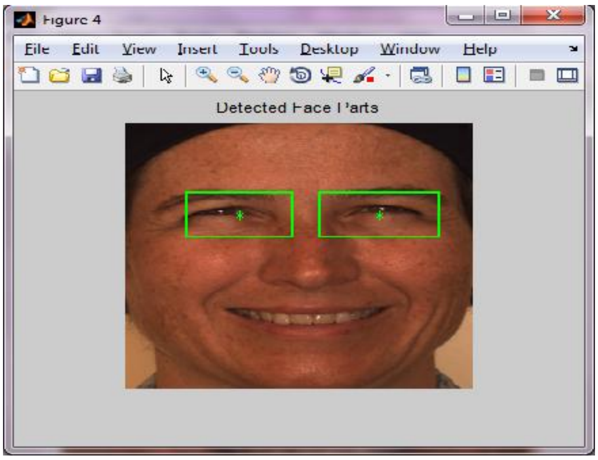

Figure 7: Face Parts Detection

CONCLUSIONS

In this paper we have to overcome the some two class problems of the fisher linear discriminant based cluster based Discriminant Analysis (CDA) process. We using clustering technique from to extract the feature values for knn classification to detect the perfect person to matching the training set of eye images. The LDA, CDA is mainly designed for two-class problems, although it canbe directly applied to multi-class problems The main difference between CDA and LDA is that LDA is designed to separate different classeswithout considering each individual cluster, while CDA exploits cluster information and separates clusters associated with different classes. Thus,CDA can handle input data with multiple clustersper class (e.g., a mixture of Gaussians) and can work well even if there is little or no difference in mean vectors

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