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Research Article

NEURAL BASED FACE DETECTION AND RECOGNITION

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ABSTRACT

The need for improved information systems has become more conspicuous, since information is an essential element in decision making. One of the major problems in the design of modern information systems is automatic pattern recognition. Face recognition is a pattern recognition task performed specifically on faces. It can be described as classifying a face either "known" or "unknown", after comparing it with stored known individuals. The great challenge for the face detection problem is the large number of factors such as pose, orientation, facial expressions, facial sizes found in the image, luminance conditions, occlusion and complexity of image's background an efficient neural network based face recognition system is proposed using nearest feature space embedding algorithm

Keywords: Face recognition, Nearest feature line, Nearest feature space, Fisher criterion, Laplacianface.

INTRODUCTION

The face is our primary focus of attention in social interaction, playing a major role in conveying identity and emotion. We can recognize thousands of faces learned throughout our lifetime and identify familiar faces at a glance even after years of separation. This skill is quite robust, despite large changes in the visual stimulus due to viewing conditions, expression, aging, and distractions such as glasses, beards or changes in hair style[1].

Face recognition is a pattern recognition task performed specifically on faces. It can be described as classifying a face either "known" or "unknown", after comparing it with stored known individuals. Computational models of face recognition must address several difficult problems. This difficulty arises from the fact that faces must be represented in a way that best utilizes the available face information to distinguish a particular face from all other faces. Faces pose a particularly difficult problem in this respect because all faces are similar to one another in that they contain the same set of features such as eyes, nose, mouth arranged in roughly the same manner.

The main contributions of this study are summarized as follows: Three factors, NFS measurement, neighborhood structure preservation, and class separability, are all considered in finding the effective and discriminating transformation matrices[2].

FACE DETECTION

Face detection is the first step of face recognition system. Output of the detection can be location of face region as a whole, and location of face region with facial features (i.e. eyes, mouth, eyebrow, nose etc.). The input image is converted into binary image to isolate the image from the background region. Segmentation is performed to localize the homogeneous parts in the image. Haar-like features that indicate specific characteristics in an image are computed with the use of integral image and Greedy Sparse LDA is applied to detect the face region in the input image[3].

SEGMENTATION

Segmentation refers to the process of partitioning a digital image into multiple segments. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

Need for Segmentation

Segmentation is a process that partitions an image into regions. In the problem of face detection, skin segmentation helps in identifying the probable regions containing the faces as all skin segmented regions are not face regions and aids in reducing the search space.

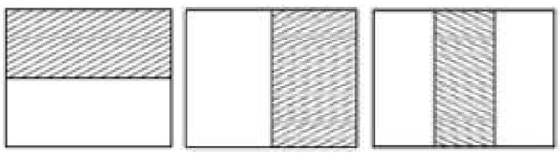
Active Contour Model based Segmentation

A novel region-based Active Contour Model (ACM) is used for segmentation which is implemented with a special processing named Selective Binary and Gaussian Filtering Regularized Level Set (SBGFRLS) method, which first selectively penalizes the level set function to be binary, and then uses a Gaussian smoothing kernel to regularize it. The

Gaussian filter can make the level set function smooth and the evolution more stable.

HAAR-LIKE FEATURES

Viola and Jones adopted the idea of using Haar wavelets and developed the Haar-like features which are rectangular features that indicate specific characteristics in an image[4]. Haar-like rectangle features are used here due to their simplicity and efficiency. Fig. **a.** shows the two rectangle and three rectangle Haar-like features .The integral image is used for the fast feature evaluation. There are two motivations for using features instead of the pixel intensities directly. Firstly, features encode domain knowledge better than pixels. The other reason is that a feature-based system can be much faster than a pixel based system.



(a)

LINEAR DISCRIMINANT ANALYSIS (LDA)

Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are two commonly used techniques for data classification and dimensionality reduction. Linear Discriminant Analysis easily handles the case where the within-class frequencies are unequal and their performance has been examined on randomly generated test data. This method maximizes the ratio of between-class variance to the within-class variance in any particular data set thereby guaranteeing maximal separability. The use of Linear Discriminant Analysis for data classification is applied to classification problem in face recognition[5].

The objective of LDA is to maximize the projected between-class covariance matrix (the distance between the mean of two classes) and minimize the within-class covariance matrix. LDA takes the number of samples in each class into consideration when solving the optimization problem, i.e., the number of samples is used in calculating the between-class covariance matrix .Hence, S_B is the weighted difference between class mean and sample mean.The within-class and between-class scatters are computed as follows.

$$S_W = \sum_{i=1}^{c} N_i (x - \mu_i)(x - \mu_i)^T$$

$$S_B = \sum_{i=1}^{c} N_i (\mu_i - \mu)(\mu_i - \mu)^T$$

$$\mu = \frac{1}{N} \sum_{i=1}^{c} N_i \mu_i$$

$$\mu_i = \frac{1}{N_i} \sum_{i=1}^{c} x$$

where

S_B	----	Between-class scatter
S_W	----	Within-class scatter
N_i	----	Number of samples in class
N	----	Total number of samples
μ_i	----	Mean of a class
μ	----	Total mean

GREEDY SPARSE LDA (GSLDA)

GSLDA works by sequentially adding the new variable which yields the maximum eigenvalue (forward selection) until the maximum number of elements are selected. Decision stumps used in GSLDA algorithm are learned only once to save computation time. In other words, once learned, an optimal threshold, which gives smallest classification error on the training set, remains unchanged during GSLDA training. The GSLDA classifier is applied as an alternative feature selection method to classical Viola and Jones' framework. The GSLDA algorithm is highly effective, capturing more variance than all algorithms currently available.

FACE AUTHENTICATION

The face authentication system utilizes a combination of two techniques: face detection and recognition. The face detection is performed on the input image and then a face classification method that uses Feed Forward Neural Network is integrated in the system. The nearest feature classifiers are used which are geometrical extensions of the nearest neighbor rule. They are based on a measure of distance between the query point and a function calculated from the prototypes, such as a line, a plane or a space[6].

PRINCIPAL COMPONENT ANALYSIS

Principal component analysis (PCA) for face recognition is based on the information theory approach. Here, the relevant information in a face image is extracted and encoded as efficiently as possible and then compared with a face database that consists of models encoded similarly and recognition is performed. A simple approach to extracting the information contained in an image of a face is to somehow capture the variation in a collection of face images, independent of any judgment of features, and use this information to encode and compare individual face images.

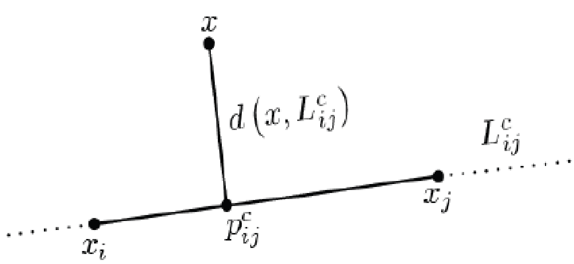
NEAREST FEATURE SPACING

The Nearest Feature Line generalizes each pair of prototype feature points belonging to the class { x_{ci} , x_{cj} } by a linear function , which is called feature line (a). The line is expressed by the span L^c_{ij} =sp (x_{ci} , x_{cj}) . The query x is projected onto L^c_{ij} as a point p^c_{ij}. This projection is computed as

$P_{ij}^{c} = X_{ci} + \tau\,(X_{cj} - X_{ci})$

$\tau = (X - X_{ci})\,(X_{cj} - X_{ci}) \,/\, \|\,(X_{cj} - X_{ci})\,\|$

The parameter τ is called the position parameter.



NFS-Distance Measurement

The distance computation from a point to a feature space is directly embedded in the projection transformation instead of the calculation during the matching phase. The nearest feature space or NFS extends the geometrical concept of NFL classifier. It generalizes the independent prototypes belonging to the same class by a feature space as $S^c = sp\,(x_{c1}, x_{c2}, \ldots\, x_{cn})$.

The query point x is projected onto the C spaces as

$P^c = X_c\,(X^{cT}\; X^c)^{-1}\; X^{cT}\, x$

where $X^c = (x_{c1}\, x_{c2}\, \ldots\, x_{cn})$

The query point x is classified by assigning it the class label ĉ, according to

$d(x,S^c) - min_{1<c<C}\, d(x,S^c) - min_{1<c<C}\, \| x - S^c \|$

Scatter Computation

The scatter computation between feature points and feature spaces are obtained and embedded in the discriminant analysis. This approach is called the NFS embedding. Two possible objective functions in the following equations are minimized:

$$F_1 = \sum_i \|\, \sum_{f(P)\in T(P)} (y_i - f^{(P)}(Y_i))\; w^{(P)}(Y_i)\, \|^2$$

$$F_2 = \sum_i \|\, \sum_{f(P)\in T(P)} \|y_i - f^{(P)}(Y_i)\|^2 \; w^{(P)}(Y_i)$$

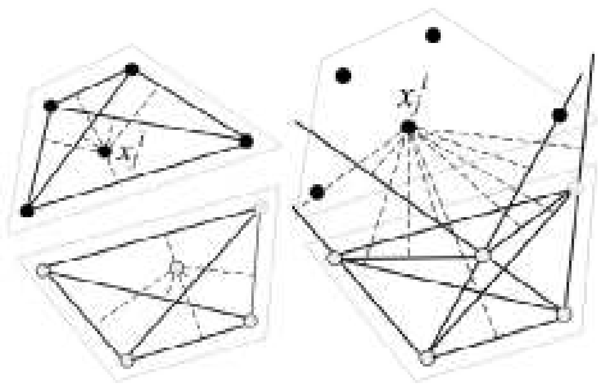
MAXIMIZATION OF THE FISHER CRITERION

Only the feature spaces with smaller distances from a specified point are used to calculate the scatters. Two parameters K1 and K2 are manually determined for the within-class scatter S_W and the between-class scatter S_B respectively. The Fisher criterion, S_B / S_W, is maximized, as shown in Fig. 3.4. Here, the training set consists of N_C classes and sample x^i_J denotes the jth sample in the ith class of size Ni. The sample in low dimensional space is obtained by a projection $y^i_J = w^T x^i_J$. The within-class and between-class scatters for the objective function F1 are calculated as

$$S_W^{(P)} = \sum_{i=1}^{Nc} \Big(\sum_{j=1}^{Ni} \Big[\Big(\sum_{f(p)\in F_{K1}^{(P)}(x_i^{(j)})} Z \Big) \Big(\sum_{f(p)\in F_{K1}^{(P)}(x_i^{(j)})} Z \Big)^T \Big]$$

$$S_W^{(P)} = \sum_{i=1}^{Nc} \Big(\sum_{j=1}^{Ni} \Big[\Big(\sum_{f(p)\in B_{K2}^{(P)}(x_i^{(j)})} Z \Big) \Big(\sum_{f(p)\in F_{K1}^{(P)}(x_i^{(j)})} Z \Big)^T \Big]$$

$$Z = w^T x_j^i - f^{(P)}(w^T x_j^i)$$



(a) (b)

$F^{(P)}_{k1}(x_j^{\,i})$ – K1 nearest feature sub-spaces generated by P feature points within the same class of point x^i_j

$B^{(P)}_{k2}(x_j^{\,i})$ – K2 nearest feature sub-spaces generated by P feature points belonging to different class of point x^i_j

Similarly the within-class and between-class scatters for the objective function F2 are calculated as

$$S_W^{(P)} = \sum_{i=1}^{Nc} \Big(\sum_{j=1}^{Ni} \Big[\Big(\sum_{f(p)\in F_{K1}^{(P)}(x_i^{(j)})} Z\; Z^T \Big) \Big]$$

$$S_W^{(P)} = \sum_{i=1}^{Nc} \Big(\sum_{j=1}^{Ni} \Big[\Big(\sum_{f(p)\in B_{K2}^{(P)}(x_i^{(j)})} Z\; Z^T \Big) \Big]$$

The optimal transformation matrix w^* is obtained by maximizing the criterion

$$w^* = argmax_w\,(S_B / S_W)$$

THE NFS EMBEDDING ALGORITHM

Input: N training samples $z_1, z_2, \ldots z_N$.

Output: The transformation matrix $w = w_{PCA} w^*$.

Step 1: Initialize the neural networks with the number of hidden layers and output layers.

Step 2: The weights between the neurons are initialized and transfer function is applied.

Step 3: Initialize four parameters P,K1,K2 and r.

Step 4: Find the projection matrix w_{PCA} by the PCA method. The sample data are transformed by matrix w_{PCA} as $x_i = w^T_{PCA}\, z_i$; i = 1, 2, . . .,N.

Step 5: Projection point generation.

1) Obtain the projection points for all feature points to the possible feature spaces $f^{(P)}(x_i)$; i = 1, 2, . . .,N.

2) Calculate and sort the distances $\| x_i - f(P)(x_i) \|$

Step 6: Compute the within-class and between-class scatters.

1) Select the K1 vectors with the smallest distances from a specified point to the feature lines within the same class.

2) K2 vectors with the smallest distances from a point to the feature lines belonging to different classes are chosen to compute the between-class scatter.

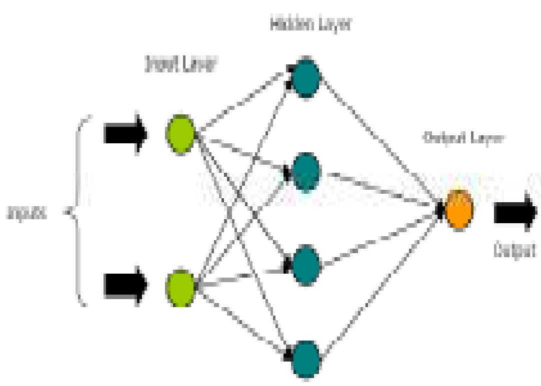
Step 7: Maximize the Fisher criterion to obtain the transformation matrix $w^* = argmax_w(S_B / S_W)$ which is composed of r eigenvectors with the largest eigenvalues.

Step 8: Calculate the transformation matrix: $w_{PCA}\ w^*$.
Step 9: Calculate the mean square error and adjust the weights till the mean square error reaches the minimum goal error.
Step 10: Test the neural network by applying test images and display the recognition output.

NEURAL NETWORKS

A Neural Network (NN) is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a connectionist approach to computation. In most cases an artificial neural network is an adaptive system that changes its structure based on external or internal information that flows through the network.

In a neural network model, simple nodes (neurons) and PEs (processing elements) are connected together to form a network of nodes, hence the term "neural network". In practical terms neural networks are non-linear statistical data modeling tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data. An artificial neural network involves a network of simple processing elements (neurons) which can exhibit complex global behavior, determined by the connections between the processing elements and element parameters. They are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. Fig. 3.5 shows general neural network architecture.



Neural networks are powerful pattern classifiers and have many similarities with statistical pattern recognition approaches. For this reason neural networks are increasingly being used in pattern recognition systems, since they have a better performance in non-linear applications. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output.

NEURAL NETWORK ARCHITECTURE FOR THE PROPOSED SYSTEM

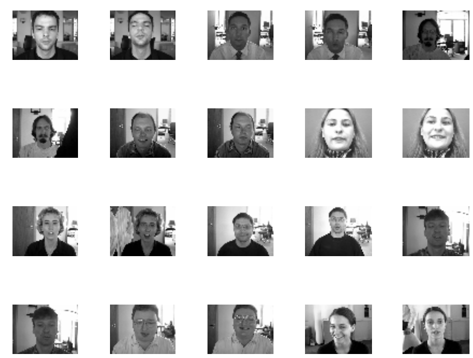
An artificial neural network is used for classification of face images. A feed forward back propagation neural network is used to perform classification. The number of input layers is 20 which is determined by the features extracted from the number of images in the training set. The hidden layer use log sigmoid activation function and the number of neurons in the hidden layer is obtained by trial and error. The output layer is a competitive layer, as one of the faces is to be identified. Fig 3.8 shows the architecture of neural network for the proposed architecture.

The network training parameters are

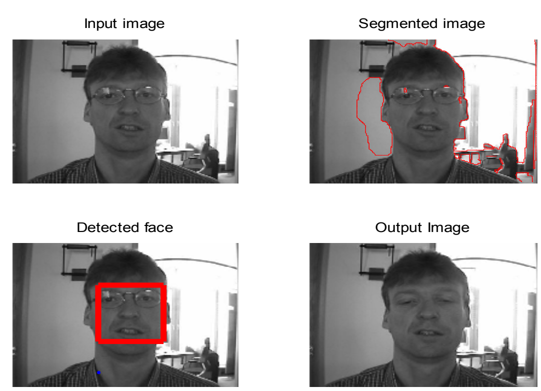
Input nodes	:	20
Hidden nodes	:	90
Output nodes	:	10
Training algorithm	:	Gradient descent
Perform function	:	Mean Square Error
Training goal	:	$10e^{-5}$
Training epochs	:	20000

EXPERIMENTAL RESULTS

This algorithm is implemented with a training set of 20 images taken from face database. Each image is in grey level and has dimensions of 384 x 286. There are ten subjects in the database. Each image is given with different expressions and face orientation. show images in the training and test images respectively. The number of training images for each person is two.The following is the training images of different persons.



The following figure shows the sample authentication output for the test image of a person with spectacles which is not used during training.



CONCLUSION

A neural network based intelligent face authentication system is proposed using Nearest Feature Space Embedding algorithm. The input face is segmented and detected using Greedy sparse LDA. The distance between the feature point and feature space is calculated and embedded in the transformation and feed forward neural networks is employed for face recognition in the proposed method. The simulation results show that the proposed scheme outperforms and is resistant to change in pose, expression and rotation. This system provides authentication insensitive to noise.

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REFERENCES

1. Ying-Nong Chen, Chin-Chuan Han, Cheng-Tzu Wang, and Kuo-Chin Fan, Face Recognition Using Nearest Feature Space Embedding, IEEE Transactions on pattern analysis and machine intelligence, 2011; 33 (6): 1073-1086.
2. Chunhua Shen, Sakrapee Paisitkriangkrai and Jian Zhang , Efficiently Learning a Detection Cascade with Sparse Eigenvectors, IEEE Transactions on Image Processing, 2011; 20 (1): 22-35.
3. S.Z. Li and J. Lu, Face Recognition Using the Nearest Feature Line Method, IEEE Transactions on neural networks, 1999; 10 (2): 439- 433.
4. P. Viola and M. J. Jones, Robust real-time face detection, International Journal of Computer Vision, 2004; 57 (2): 137–154.
5. J. Yang, D. Zhang, A. Frangi, and J. Yang, Two-Dimensional PCA: A New Approach to Appearance-Based Face Representation and Recognition, IEEE Transactions on pattern analysis and machine intelligence, 2004; 26 (1): 131-137.
6. Wei-Shi Zheng, Jian-Huang Lai, and Pong C. Yuen , GA-Fisher: A New LDA Based Face Recognition Algorithm With Selection of Principal Components, IEEE Transactions on systems, man, and cybernetics—part B: cybernetics, 2005; 35 (5).

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