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Face Recognition using Rectangular Feature

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Abstract- Face recognition is the broad area of researchers for exploring new techniques. The main part of the face recognition is feature extraction. Feature extraction is the form of dimensionality reduction. When the input data to an algorithm is too large to be processed then the input data will be transformed into a reduced representation set of features. Transforming the input data into the set of features is called feature extraction. For the feature extraction and image processing we use rectangular feature. The rectangular feature is the techniques where we have consider pixel values of the gray scale image. In the rectangular feature x_{min}, y_{min}, height and width are considering for calculation the pixel values on particular point in an image. We have to calculate face feature vector using principal component analysis (PCA). We have taken three features eyes, lips and nose for feature extraction these features are used for face recognition. On these four rectangular features we have to applied PCA algorithm for dimensionality reduction then feature vectors used for classifier. Then we have to train RBFNN (radial basis function neural network) for classifying the output. Result comes in the form of recognition rate.

Index Terms—Face detection, Face recognition, Image processing, Machine learning and Rectangular feature.

1. Introduction

Face recognition has received significant attention in the last 15 years, due to the increasing number of commercial and law enforcement applications requiring reliable personal authentication (e.g. access control, surveillance of people in public places, security of transactions, and human-computer interaction) and the availability of low-cost recording devices. The system recognizes an individual by matching the input image against images of all users in a database and finding the best match. Although great advances have been achieved, Recognition of face images with large variations of pose, illu Mination and expression is still a challenging task.

There are mainly two approaches to represent face images. One is the holistic methods such as PCA and LDA. The other is local features such as rectangular features. Rectangular features are used for feature extraction. Recently Rectangular features have drawn increasing attention in face recognition because they can capture rectangular features in face images for training of the system. In this paper, we present an RBFNN-based face recognition system for recognizing front-view face images. The standard feed forward back propagation algorithm is used to simultaneously perform hit-miss transformation, train, and classify features within the same iteration. The recognized image is determined by the corresponding output value that lies within a certain threshold. We have also extended the system to detect the position of eyes.

Rectangular features are cropped from face images for creation of face database for PCA algorithm. PCA algorithm is applied on this rectangular feature for getting feature vector. We resizing the cropped image in 24x24 for four rectangle cropped image. This feature vector is used for training the neural network for finding minimum distances that comes in the form of numerical values. For testing, we use a total of a hundred face images from ten individual subjects. Each of them has his own set of ten images. Not one image is repeated. Each image varies in orientation and expression. In some sets, there are face images with and without glasses. The paper is not just about being able to generalize facial expressions, orientations, and occlusions. Any healthy neural network has no problem with that.

We aim for a more robust network. Criteria for evaluation mainly include the ability to generalize results to accommodate changes in gray-level intensity and noise. This paper shows the new method for face detection and recognition that is based on rectangular feature. There are many methods for face recognition but we implement this method for accurate face recognition using RBFNN. We used gradient decent algorithm as training algorithm the gradient descent method is simple because it only requires the calculation of the gradient.

2. Rectangular Feature From Adaboost

In this section we explain about rectangular feature that what it is and how it gets. This rectangular feature is used for getting feature vector.

2.1. Rectangular crop

It is easiest to crop image in rectangular form because we have to just select two coordinates on the image and using MATLAB we decide other two coordinates and the image is cropped in rectangular format. The rectangular feature is useful for face detection because it is the first step of any face Recognition system. So we detect the face using rectangular feature. In image processing technique we consider any image as multi dimensional matrices depending on the format of the image. The task that can be performed by image processing is color correction, compression decompression of the image, image recognition and image cropping.

We can get rectangular features easily using MATLAB and mathematical function that is x and y coordinates of the cropped image. The rectangular features are the feature which sums the pixels in rectangular area and involving in sum of image pixel area.

Figure1. Rectangular features from adaboost

2.2. Square crop

To crop any image in square form we have to define two points on the image for corner points and then we define points by this coordinate such that x=y=d, where d is some constant.

3. ALGORITHM USED FOR FEATURE EXTRACTION

In this section we have to show that how higher dimensional features (data) are reduced to lower dimensional features.

3.1. Principal component analysis

Principal component analysis (PCA) is a mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has as high a variance as possible (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it be orthogonal to (uncorrelated with) the preceding components. Principal components are guaranteed to be independent only if the data set is jointly normally distributed. PCA is sensitive to the relative scaling of the original variables.

The algorithm used for principal component analysis is as follows.

i. Acquire an initial set of K face images (the training set) &Calculate the eigenfaces from the training set, keeping only k' eigenfaces that correspond to the highest eigenvalue.
ii. Calculate the corresponding distribution in k'-dimensional Weight space for each known individual, and calculate a set of weights based on the input image.
iii. Classify the weight pattern as either a known person or as unknown, according to its distance to the closest weight vector of a known person.

Let the training set of images be λ_1, $\lambda_{2,} \ldots \lambda_K$ then the average set of face can be defined by

$$\Psi = \frac{1}{K}\sum_{n=1}^{K} \lambda n \qquad \text{...... (1)}$$

The average is differ by the different face in image vector

$$\Phi_i = \lambda_i - \Psi \qquad \text{...... (2)}$$

The co-variance matrix is formed by

$$C = \frac{1}{K}\sum_{n=1}^{K} \Phi_n . \Phi^T_n = A.A^T \qquad \text{......(3)}$$

Where the matrix A = $[\phi_1, \phi_2, \ldots\ldots, \phi_K]$.

3.2. Feature extraction

Feature extraction transforms the data in the high dimensional space to a space of fewer dimensions. The data transformation may be linear, as in principal component analysis (PCA), but many nonlinear dimensionality reduction techniques also exist. The main linear technique for dimensionality reduction, principal component analysis, performs a linear mapping of the data to a lower dimensional space in such a way that the variance of the data in the low dimensional representation is maximized. In practice, the correlation matrix of the data is constructed and the eigenvectors on this matrix are computed. The eigenvectors that correspond to the largest eigenvalues (the principal components) can now be used to reconstruct a large fraction of the variance of the original data.

3.3. Preprocessing and normalization

In preprocessing image data are converted in to an acceptable form for analysis. In this image is converted in to better form of feature extraction. It improves the quality of input data so we have to do pre-processing. It manages the intensity of image, contrast, brightness and noise reduction.

Normalization is like pre-processing in this we manage mean removal, image resizing and contrast adjustment of the image it is also called the dynamic range expansion and it has set the contrast of the image on gray scale. The main purpose of normalization is to sense the different type of image in desired range of intensity of the image and it more familiar to desired range of sensing the image or normal the image. Normalization is a linear process. If the intensity range of the image is 50 to 180 and the desired range is 0 to 255 the process entails subtracting 50 from each of pixel intensity, making the range 0 to 130. Then each pixel intensity is multiplied by 255/130, making the range 0 to 255.

4. DIFFERENT APPROACH OF FACE RECOGNITION

4.1. Face detection

Face detection is the first stage of an automatic face recognition system, since a face has to be located in the input image before it is recognized. A definition of face detection could be: given an image, detect all faces in it (if any) and locate their exact positions and size. Usually, face detection is a two-step procedure: first the whole image is examined to find regions that are identified as “face”. After the rough position and size of a face are estimated, a localization procedure follows which provides a more accurate estimation of the exact position and scale of the face. So while face detection is most concerned with roughly finding all the faces in large, complex images, which include many faces and much clutter, localization emphasizes spatial accuracy, usually achieved by accurate detection of facial features.

4.2. Face recognition

Face recognition techniques can be roughly divided into two main categories: global approaches and feature based techniques. In global approaches the whole image serves as a feature vector, while in local feature approaches a number of fiducially or control points are extracted and used for classification.

i. Global Approaches for Face Recognition

Global approaches model the variability of the face by analysing its statistical properties based on a large set of training images. Representative global techniques are Eigen faces, linear discriminant analysis (LDA), Support Vector Machines (SVM) and neural networks. The first really successful face recognition method (and a reference point in face recognition literature) is a holistic approach based on principal component analysis (PCA) applied on a set of images in order to extract a set of Eigen-images, known as Eigen faces. Every face is modelled as a linear combination of a small subset of these Eigen faces and the weights of this representation are used for recognition.

ii. Feature Based Face Recognition Techniques

The main idea behind feature-based techniques is to discriminate among different faces based on measurements of structural attributes of the face. Most recent approaches are the Embedded Hidden Markov Models (EHMMs), the Elastic Graph Matching and Dynamic Link Architecture. For frontal views the significant facial features appear in a natural order from top to bottom (forehead, eyes, nose, and mouth) and from left to right (e.g. left eye, right eye). EHMMs model the face as a sequence of states roughly corresponding to facial features regions. The probability distribution functions of EHMM states are approximated using observations extracted by scanning training images from left-to-right and top-to-bottom. To verify a face, first the observations are extracted from the input image and then their probability given the stored EHM model is calculated.

5. Training Algorithm And RBFNN

In this section we describe about the training algorithm and RBFNN (radial basis function neural network) it is our neural network classifier.

5.1. Gradient decent algorithm

The steepest descent method, also known as the gradient descent method, forms the basis for many direct methods used in optimizing both constrained and unconstrained problems. The following describes how the technique works. Let us declare an arbitrary initial weight vector X. We would like to have the performance index decreased with every iteration, that is $F(X_{k+1}) < F(X_k)$. The steepest gradient concept is about how to select the directional vector P_k so that for a sufficiently small learning rate α_k the index will decrease. The steepest descent method is simple because it only requires the calculation of the gradient. It is guaranteed to converge to a stationary point if the learning rate is small enough. The training time for gradient descent is normally longer than other algorithms.

5.2. Radial basis function neural network

A radial basis function network is an artificial neural network that uses radial basis functions as activation functions. It is a linear combination of radial basis functions. They are used in function approximation, time series prediction, and control. A Radial Basis Function (RBF) neural network has an input layer, a hidden layer and an output layer. The neurons in the hidden layer contain Gaussian transfer functions whose outputs are inversely proportional to the distance from the canter of the neuron. RBF networks are similar to K-Means clustering . The main difference is that PNN/GRNN networks have one neuron for each point in the training file, whereas RBF networks have a variable number of neurons that is usually much less than the number of training points. Although the implementation is very different, RBF neural networks are conceptually similar to K-Nearest Neighbour (K-NN) models. The basic idea is that a predicted target value of an item is likely to be about the same as other items that have close values of the predictor variables. The neurons in the hidden layer contain Gaussian transfer functions.

5.3. Training of RBF networks

The following parameters are determined by the training process:

i. The number of neurons in the hidden layer.
ii. The coordinates of the center of each hidden-layer RBF function.
iii. The radius (spread) of each RBF function in each dimension.
iv. The weights applied to the RBF function outputs as they are passed to the summation layer.

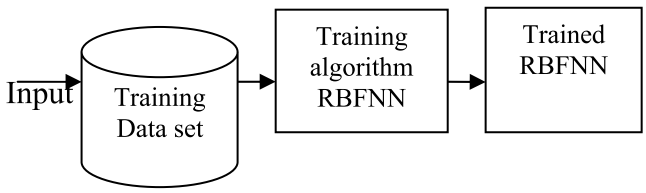

Figure2. Training of RBFNN algorithm

Figure3. Training set

6. DIFFERENT CLASSIFIER

Weak Classifier

Weak classifier is the atomic component in our classifier structure. After the first time of training, weak classifier s are constructed. One classification function represents one feature of particular scale, position, and a specific color domain. The classification function will be weighted according their correctness. However, these classifiers are so un-reliable that they are called “weak classifiers”. They can no t classify the training data well before any refinement. Here we adapt a boosting algorithm is base on a variant of the AdaBoost Algorithm modified by Viola. In the original boosting concept, a weak classifier only needs to classify correctly slightly better than chance. With aid of AdaBoost algorithm, a designer can continue adding different weak classifiers to achieve desired low training error.

6.1.1. Strong Classifier

The classification functions selected and constructed by AdaBoost Algorithm are called “the strong classifiers”, with the meaning of having higher accuracy than the weak classifiers. One strong classifier is formed by several weighted weak classifiers. Weight of each classifier is decided according to the detection r ate of the classifier Being different to weak classifiers; strong classifiers are additionally trained with those sub-images accepted by previous trained strong classifiers. Generally, the mechanism will make the classifiers be able to correct the false positives done by the previous one.

Strong classifiers can per for m detecting task with good accuracy by themselves, with accuracies of 60% to 85%. However, this result is not good enough for our detector. So, we organize them in to a cascade classifier structure to perform in a better accuracy and speed.

6.2. Training of Classifier using Rectangular Features

We can train the classifier using rectangular feature that is very useful for the classification in the training of classifier our area of interest is the generalization error and training error. We have to know about the generalization error and training error and how to resolve this problem for improving the classification problem and because of this we can use adaboost fast feature evaluation method to show the results of classifier and its performance. We can improve the performance of classifier to show again and again using the steps of classifier and many rounds of the feature should be calculated we can use more features to show the results single feature is not enough for discriminate the faces to non-faces we can use many features of a face that should be useful for the classifying different features.

7. EXPERIMENTAL RESULTS

We can apply the proposed face recognition method on ORL face data set for separating the ten data set classes. For all experiments we used the mat lab technical computing for code running on a pc with Intel Pentium 4 dual core, 2.0-GHZ CPU and 1024-Mb RAM. Before doing any experiment, we cropped the input images to reduce their size to 24×24. Our selected dataset contains grayscale images of 10 subjects in BMP format. In these experiments, we considered 30 images per each subject (total 300 images) containing different illumination and different poses, which 30 images of each used for training and also 30 images used for testing the method. As mentioned we repeat the same experiment by extracting 30, 25, 20, 15, 10 and 5 features and compared the identification rate of the proposed method. So we have to use RBFNN as proposed method it made the perfect face recognition system.

It is clear that overlapped classes may be are separable in remaining (not shown) 6 dimensional subspaces (it is not possible to demonstrate face images in nine dimensional space and only to get a sense about performance of the method) To improve the accuracy of the method for face classification, projected face images are given to a neural network. This neural network consists of three layers, 10 neurons in the first layer, 20 neurons in the hidden layer and one neuron in the output layer. We normalize the images on different size that are 100x100, 150x150 and 200x200. We have to compare the recognition rate on different size that which size gives the better recognition rate of the system.

Output of the neural network is a 16×1 vector that each element of that vector represents similarity of the input image to one of 10 available classes Similarity is between zero and one and the input image is classified to the class that has the greatest similarity to it. 30 images from each class (totally 300 images) are used for network training and same images from each class (totally 300 images) are used for testing the proposed method. As mentioned before, the above experiment repeated for different values of PCA eigenvectors.

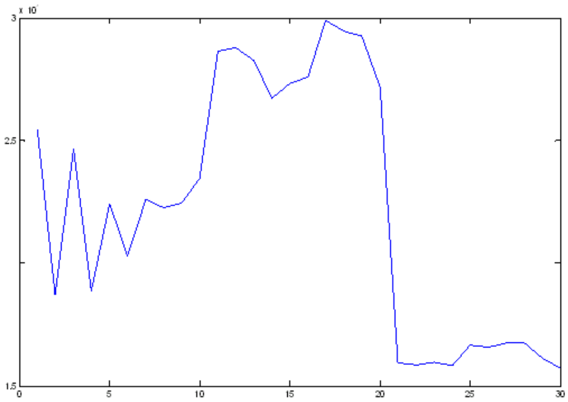

Figure4. Spread constant values

In out paper we considered rectangular feature for detection purpose figure one is the kind of some rectangular features figure two is the block diagram of our proposed neural network classifier. In our paper totally research based improvement of face recognition method. Figure three is the training set from the ORL face image database through this training set gives training and compare with testing set that identifies the correct face in the form of recognition rate. Figure five show the recognition rate of RBFNN algorithm that shows in percentage that corresponding to number of features. In this we used different normalized size 100x100, 150x150, 200x200 fifteenth features given good recognition rate. Figure sixth and seven have different recognition values classifying the face.

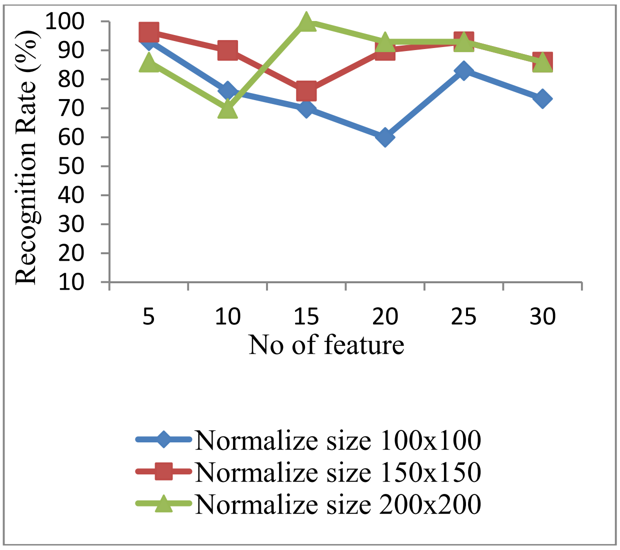

Figure5. Recognition rate for RBFNN of different normalize size

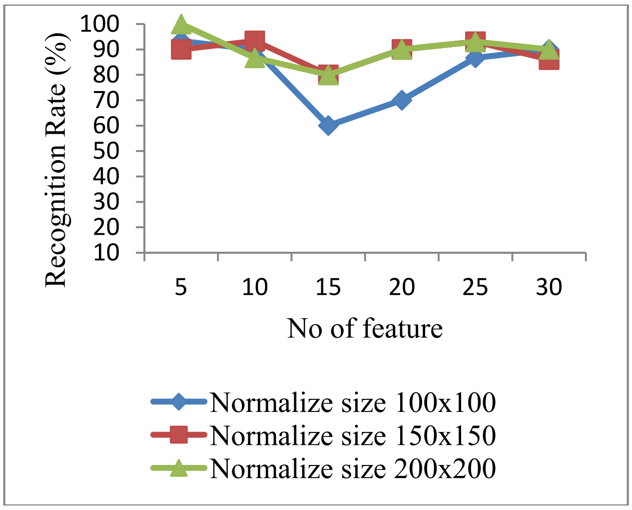

Figure6. Recognition rate for RBFNN to corresponding no of feature

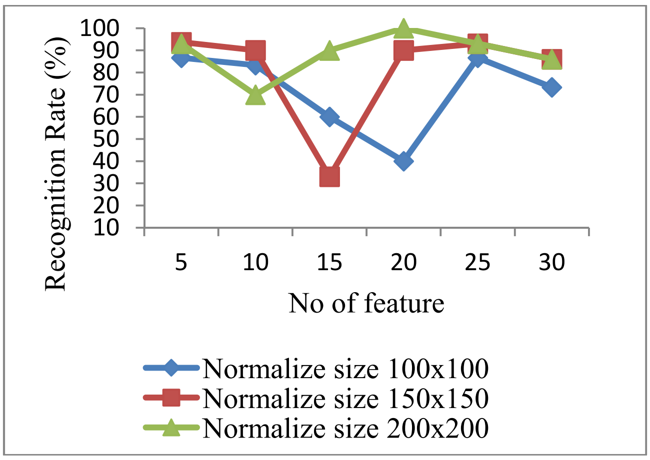

Figure7. Recognition rate for RBFNN algorithm of different normalize size.

8. Conclusion

In this paper, we generalize the things that are useful for the face detection and recognition based on the rectangular feature. The rectangular feature is used for the face detection purpose and feature extraction. PCA is also used for calculating feature vector to make matrix of the face data. These matrix is used for the compare the values to the other matrix and formed correlation matrix. Images are converted in to columns in the form of data that data are used for input to our classifier. Inputs are in the form of numerical values our proposed method gives the better results in the form of recognition rate that is in percentage. For classifying we used RBFNN as classifier. In rectangular feature we consider eyes, lips, nose as a rectangular feature for this we did normalization process. On this rectangular feature we applied PCA algorithm for calculating feature vector. We used different size of the face image ORL database is used for the training and testing of the system. The size is 100x100, 150x150 and 200x200. Based on the experiment we found 200x200 is gives better recognition rate and fifteenth number of feature gives good recognition rate.

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