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Pose invariant Face Recognition using Neural Networks and PCA

Prof. Nagarkar Raviraj Prakash, TPO, BMIT, Solapur

Dr. Kazi Kutubuddin Sayyad Liyakat, Associate Professor,BMIT, Solapur

Abstract-

In this paper, human face as biometric is considered. Original method of feature extraction from image data is introduced using feed forward **Neural networks** (multilayer perceptron) and **PCA** (principal component analysis). This method is used in human face recognition system and results are compared to face recognition system using **PCA** directly, to a system with direct classification of input images by Neural network, and to a system using **NN** as a feature extractor and **NN** network in the role of classifier. In order to obtain deeper insight into eight presented methods, also visualizations of internal representation of input data obtained by neural networks are presented.

Keywords:- Eigen values, face Recognition, PCA, EPOCH, Neural networks

Principal Component Analysis: -

Principal component analysis PCA [1] is a standard statistical method used for feature extraction. It transforms input data represented by a random vector x = $[x_0, x_1, x_2, \ldots, x_{p-1}]^T$, E[x]= 0 with correlation matrix $\mathbf{R}_X = E[XX^T] = R^T_X$ to a set of coefficients (principal components)

$$a_j = \mathbf{u}_j^T \mathbf{x} = \mathbf{x}^T \mathbf{u}_j,\ j = 0,1,\ldots,p-1$$

represented by the vector a = [ao,a1,a2 ,..., ap-l $]^T$. Unit vectors $u_j = [u_{j0}, u_{j1}, u_{j,2} \ldots, u_{jp.1}]^T$ $(\|\mathbf{u}\| = \sqrt{\mathbf{u}^T\mathbf{u}} = 1)$ form the matrix U = [**uo, u1, u2**, ._.**u p-l**] and they are eigenvectors of the correlation matrix $\mathbf{R}_X$, associated with the eigen values

$$\lambda_0, \lambda_1, \ldots, \lambda_{p-1},\ \text{where}\ \lambda_0 > \lambda_1 > \ldots > \lambda_{p-1}\ \text{and}\ \lambda_0 = \lambda_{MAX}.$$

The most important eigenvectors are those corresponding to largest eigen values of R_X

The representation of input data (analysis, forward transform) is defined by

$$\mathbf{a} = \mathbf{x}^T \mathbf{U} = \mathbf{U}^T \mathbf{x}$$

and synthesis (inverse transform) is represented by

$$\mathbf{x} = \mathbf{U}\mathbf{a} = \sum_{j=0}^{p-1} a_j \mathbf{u}_j$$

It is possible to represent input data by a reduced number of principal components (dimensionality reduction). The transform uses eigenvectors corresponding to largest eigenvalues of R_X, and those corresponding to small eigenvalues are discarded

$$\mathbf{x}' = \sum_{j=0}^{m-1} a_j \mathbf{u}_j\ .\ m < p$$

Then vector x' is an approximation of x, while

$$\lambda_0 > \lambda_1 > \ldots > \lambda_{m-1} > \lambda_m > \ldots > \lambda_{p-1}.$$

Feed Forward Multilayer Perceptron:-

Basic multilayer perceptron **(MLP)** building unit is a model of artificial neuron. This unit computes the weighted sum of the inputs plus the threshold weight and passes these sums through the activation function (usually sigmoid) **[1]:**

$$v_j = \theta_j + \sum_{i=1}^{p} w_{ji}x_i = \sum_{i=0}^{p} w_{ji}x_i$$

$$y_j = \varphi_j(v_j)$$

where v_j is linear combination of inputs xl,x2, ..., xp of neuron j , $w_{jo} = \theta_j$ is threshold weight connected to special input xo = - 1 , y_j is the output of neuron j and $\psi_j(.)$ is its activation function. Herein we use special form of sigmoidal (non-constant, bounded, and monotone-increasing) activation function - logistic function

$$y_j = \frac{1}{1+\exp(-v_j)}$$

In a multilayer perceptron, the outputs of the units in one layer form the inputs to the next layer. The weights of the network are usually computed by training the network using the hack propagation (BP) algorithm. A multilayer perceptron represents nested sigmoidal scheme [I], its form for single output neuron is

$$F(\mathbf{x},\mathbf{w}) = \varphi\left(\sum_j w_{oj}\varphi\left(\sum_k w_{jk}\varphi\left(\dots\varphi\left(\sum_i w_{li}x_i\right)\dots\right)\right)\right)$$

where $\varphi(\cdot)$ is a sigmoidal activation function, w_{oj} is the synaptic weight from neuron j in the last hidden layer to the single output neuron ***0,*** and so on for the other synaptic weights, xi is the ***i*** -th element of the input vector **x** . The weight vector w denotes the entire set of synaptic weights ordered by layer, then neurons in a layer, and then number in a neuron.

FACE DATABASE

We use the face database from Yale database, which consists of face images of 15 people (shown in Fig. I), 10 for each person under various passions & scale. It means, total number of face images is 150. Each image is 240 X 320 pixels, eight-bit grayscale. An example of different face images (patters) belonging to the same class is shown in Figure bellow.

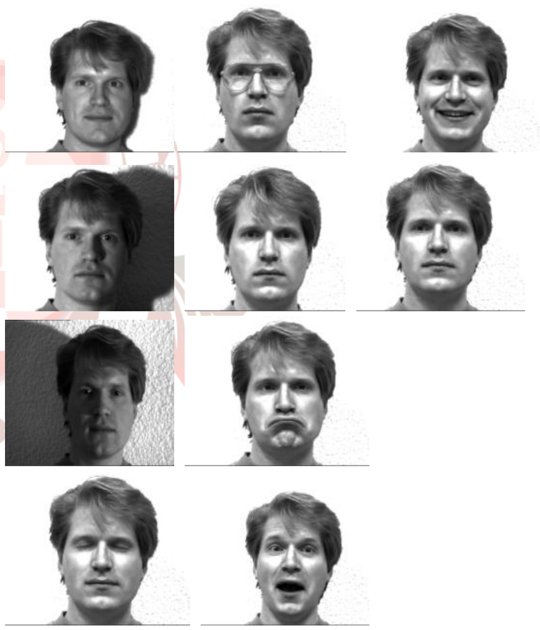
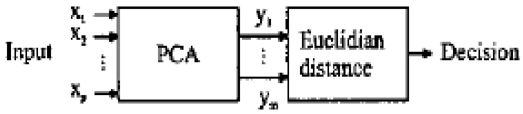


Figure: - The Subject with different eleven poses used in project as per Yale database

Recognition method: -

PCA applied directly to face images with Euclidian distance as a classification measure, shown in figure bellow. The correlation matrix was computed from 8 training faces and for classification first 8 eigenvectors of the correlation matrix are used 93.54 % of test faces was recognized successfully. This result corresponds to method as shown in figure bellow.



K-nearest neighbor algorithm: -In pattern recognition, the k-nearest neighbor algorithm (k-NN) is a method for classifying objects based on closest training examples in the feature space. k-NN is a type of instance-based learning, or lazy learning where the function is only approximated locally and all computation is deferred until classification. It can also be used for regression. The best choice of k depends upon the data; generally, larger values of k reduce the effect of noise on the classification, but make boundaries between classes less distinct. A good k can be selected by various heuristic techniques, for example, cross-validation. The special case where the class is predicted to be the class of the closest training sample (i.e. when k = 1) is called the nearest neighbor algorithm. The accuracy of the k-NN algorithm can be severely degraded by the presence of noisy or irrelevant features, or if the feature scales are not consistent with their importance. Much research effort has been put into selecting or scaling features to improve classification. A particularly popular approach is the use of evolutionary algorithms to optimize feature scaling. Another popular approach is to scale features by the mutual information of the training data with the training classes

The nearest neighbor algorithm has some strong consistency results. As the amount of data approaches infinity, the algorithm is guaranteed to yield an error rate no worse than twice the Bayes error rate (the minimum achievable error rate given the distribution of the data). k-nearest neighbor is guaranteed to approach the Bayes error rate, for some value of k (where k increases as a function of the number of data points). The k-NN algorithm can also be adapted for use in estimating continuous variables. One such implementation uses an inverse distance weighted average of the k-nearest multivariate neighbors. This algorithm functions as follows:

1. Compute Euclidean distance from target plot to those that were sampled.
2. Order samples taking for account calculated distances.
3. Choose heuristically optimal k nearest neighbor based on RMSE done by cross validation technique.
4. Calculate an inverse distance weighted average with the k-nearest multivariate neighbors.

Epoch (astronomy): -In astronomy, an epoch (or sometimes epochal moment) is a moment in time for which celestial coordinates or orbital elements are specified. In the case of celestial coordinates, and with modern technology, the position at other times can be computed by taking into account precession and proper motion. In the case of orbital elements, it is necessary to take account of perturbation by other bodies in order to calculate the orbital elements for a different time.The currently used standard epoch is J2000.0, which is January 1, 2000 at 12:00 TT. The prefix "J" indicates that it is a Julian epoch. The previous standard epoch was B1950.0, with the prefix "B" indicating it was a Besselian epoch.

Result:- With the help of this method, the result can be reach upto 92% irrespective of the poses of the subject. If number of epoches are increased the result is good. For lesser epoches, result is upto 78% . So we consider the epoches are upto 1000.

Conclusion : -

The main limitation of the current system is that it only detects upright faces looking at the camera. Separate versions of the system could be trained for each head orientation, and the results could be combined using arbitration methods similar to those presented here. Preliminary work in this area indicates that detecting profiles views of faces is more difficult than detecting frontal views, because they have fewer stable features and because the input window will contain more background pixels. We have also applied the same algorithm for the detection of car tires and human eyes, although more work is needed. Even within the domain of detecting frontal views of faces, more work remains. When an image sequence is available, temporal coherence can focus attention on particular portions of the images. As a face moves about, its location in one frame is a strong predictor of its location in next frame. Standard tracking methods, as well as expectation-based methods, can be applied to focus the detector's attention. Other methods of improving system performance include obtaining more positive examples for training, or applying more sophisticated image preprocessing and Normalization techniques. This paper illustrates the use of neural network for face recognition which gives the improved result as compared to conventional face recognition methods.

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