A SURVEY ON SINGLE IMAGE PER PERSON PROBLEM IN FACE RECOGNITION

Dr. C. Rajakumar
Associate Professor, Department of ECE, Anurag Group of Institutions, Hyderabad

Abstract

Face recognition is type of biometric used to identify a human being. The advantage of Face recognition compared to another recognition method such as finger print recognition are palm print recognition is there is no physical contact between face and image capturing device.In Face recognition there are lot issues are there.One of the major issue in Face recognition problem is one sample problem . One sample problem exists in passport, driving license etc.Lot of algorithms developed to sove this one sample issue. Techniques like svd,qr,sdd and gabor filter approach have been developed. But recognition rate and training time is still a challenging problem. Here all the methods are analysed based on their performance.

1. Introduction

Normally, only one face sample per person is available in cases such as driving license, passport and law enforcement. Adding more samples of same person in the database faces memory requirement problem and is also expensive. This is one sample per person problem. One sample per person is like a small sample size problem in pattern recognition and machine learning. Training images are nothing but stored face images in the database. The current face recognition technique faces difficulty in collecting samples. Many face recognition algorithms fail if the training sample is one. Face images of various persons are stored in face database. The goal is to recognize an individual with varying pose, lightning condition and facial expression from the stored database. Many researchers addressed different techniques to recognize a known face from the one sample. The advantages of one sample problems are Collecting the samples is easy and storing one samples of each person in a face database is easy. Feature extraction, pre processing and normalization operation requires more computational time for multiple training images of a person. These factors can be reduced for single training image per person.

2. Literature Suvey

To recognize a face, geometric features alone are not sufficient. These problems are addressed by several researches. Manjunath et al (1992) introduced a new method for facial feature extraction and representation. Chen et al (2004) proposed new approach for single training image per person problem. The author partitioned each image into set of sub images. The size of sub image may be 5×5 or 5×3 with a dimensionality 25 or 15. A new training set for each class is obtained. The testing image is also partitioned into non-overlapping pattern. All the patterns are projected to generate the projected sub pattern and classification is based on nearest neighbour classifier. This method gives better accuracy than other previous approaches. Chen et al (2004) proposed enhanced $(PC)^2A$ in two directions. To get more information from the original image, its first-order projection and its second order projection are combined. PCA is performed on the training set.Experimental resultsshows that enhanced $(PC)^2A$ approach increases its performance with 3.5% than $(PC)^2A$ method. To obtain multiple training sample from single face, Yin (2006) demonstrated a new method in which sampling is done to obtain multiple images. Applying Fisher Linear Discriminant Analysis(FLDA) to the training and testing set provides a better recognition rate than conventional methods. Li

& Pan (2007) proposed a new face recognition technique named as 2D(PC)^{2}A to solve one sample problem.

Another approach is a combination of local and holistic method. How to combine these methods is a challenging research issue in one sample problem. The work carried out in this direction is still at infancy. Hence, there is a huge potential to carry out research work in this direction.

3. SVD Approach

Singular Value Decomposition (SVD) decomposes a matrix into product of three matrices. Let A be $m \times n$ matrix. Then SVD of $A=U\Sigma V^T$, where U and V are orthogonal matrix and Σ is a diagonal matrix. The elements in Σ are singular values of A. For a symmetric matrix, the SVD decomposition(Golub&Vanloan 2012) is $A=Q\Sigma Q^T$ where Q is orthogonal matrix. SVD decomposes a matrix into sum of rank-1 matrices. This means

$$A = \sum_{i=1}^{i=r} \sigma_i u_i v_i^T$$

$A = \sigma_1 u_1 v_1^T + \sigma_2 u_2 v_2^T +,...,+ \sigma_r u_r v_r^T$ where r is the rank of the matrix and $u_1, u_2, u_3, ... u_m$ represents columns of U and $v_1, v_2, v_3, \ldots, v_n$ represents columns of V. SVD gives the optimal rank-k approximation by setting all the r-k least singular values to zero. In SVD, the matrices U and V may be non-negative.

4. QR Approach

QR decomposition (Lay 2000) is one type of matrix factorization. It is applicable to square and rectangular matrices. It factorises the matrix into a product of orthogonal and upper triangular matrix. This factorization is unique for non singular square matrix.Let A be a matrix. QR decomposition of A is given by **A=QR** The size of Q is $m \times m$ and the size of R is $m \times n$. Hence the column of A and columns of Q are the basis for column space of A. This can be stated that $A = [a_1, a_2, ... ,a_n]$, then Span $[a_1, a_2, ...,a_n]$ = span $[q_1,q_2,...,q_n]$.The absolute values of diagonal elements of R are in descending order in QRCPdecomposition. In QRCP decomposition columns of A are selected based on permutation matrix denoted by P and $Q^TAP=R$

5. SDD Approach

Semi discrete decomposition decomposes a matrix (Kolda&O'leary 1999) into product of three matrices. This decomposition requires less storage than other methods such as SVD.Let A be the matrix of an image A and its size be $m \times n$. Let the matrix A be approximated by SDD decomposition. Let the k-th term SDD of Abe A_k. Then $A_k=X_kD_kY_k$.

$$A_k = \left[x_1 x_2, ..., x_k \right] \begin{bmatrix} d_1 & 0 & ... & 0 \\ 0 & d_2 & ... & 0 \\ ... & ... & ... & ... \\ 0 & 0 & ... & d_k \end{bmatrix} \begin{bmatrix} y_1^T \\ y_2^T \\ ... \\ y_k^T \end{bmatrix}$$

The size of X_k is $m \times k$ and size of Y_k is $n \times k$ and D_k is a diagonal matrix. SDD provides more accurate approximation by storing fewer coefficients. The k-th term SDD stores $k(m+n)$ entries from the set. Each x_i is a column vector. The entries in the vector are from the set $S=\{-1, 0, 1\}$. Each y_i is a $n \times 1$ column vector. The columns of X_k and Y_k may be linearly independent or dependent. Number of zeros in X_k and Y_k may be larger than number of non zero elements. X_k and Y_k may be ternary

6. Gabor filter Approach

In this approach, Gabor filter banks with 5 scales and 8 orientations are considered and magnitude response is shown in figure 1. Convolution of Gabor filter with an image is shown in figure 2

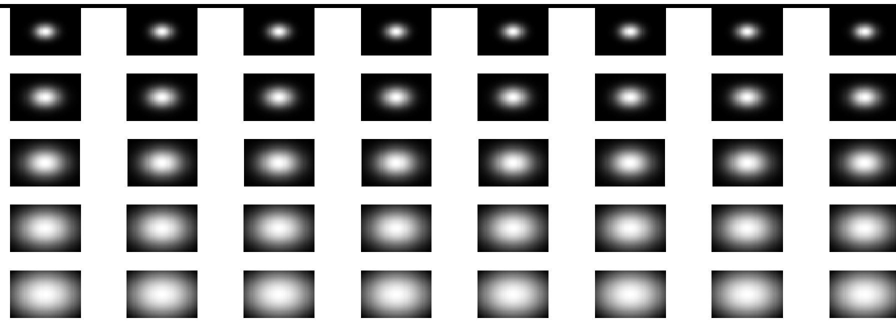

Figure 1 -Magnitude Response of Gabor Filter

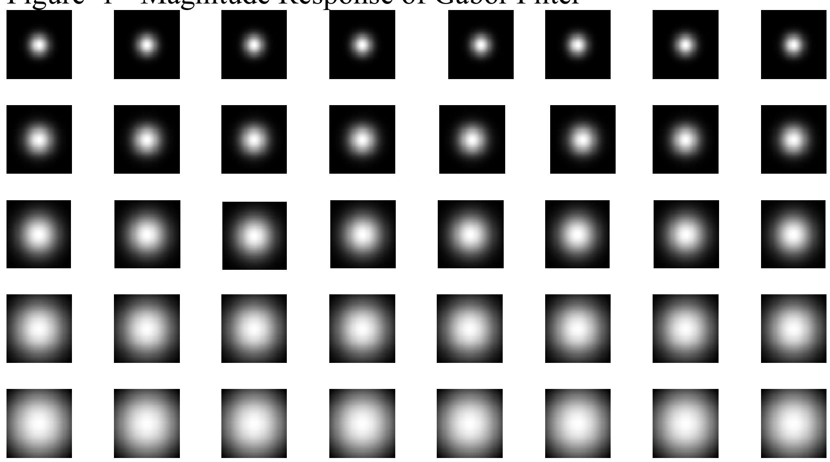

Figure 2 Convolution Response

7. Experimental Results

ORL and YALE databases are considered . The rank of the original image is 92. The size of all the image is 112×92.Sample image of ORL database is shown in figure 3 and number of classes are 40.Recognition rate of this method is shown in figure 4

Figure -3 Sample Images ORL Database

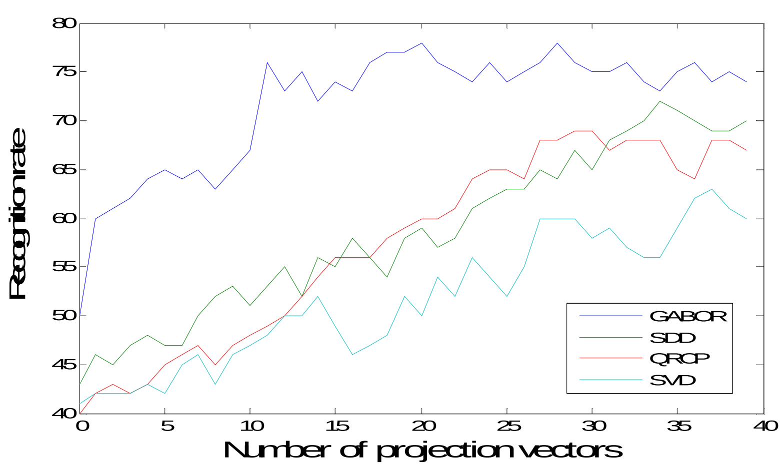

Figure 4 Recognition Rates of ORL Database

Gabor filter outperforms all the other methods. The size of the image is 120×110. Total number of classes is 15. The size of the X is 110×110. Sample image of YALE database is shown in figure 5 Recognition rates of is shown in figure 6

Figure -5 Sample Images YALE Database

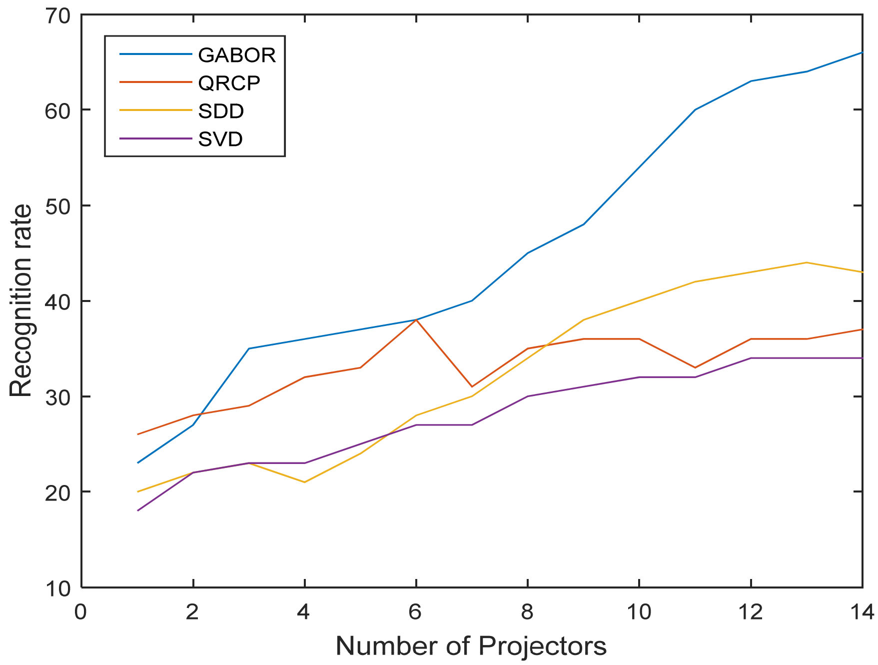

Figure 6 Recognition Rates in YALE Database

7. Conclusion and Future Work

Single image per person is a challenging issue in face recognition . Even though many research is going on , attaining 80 % recognition is a difficult one.Out of all methods specified recognition rate of gabor filter is very much higher than other methods. To improve the recognition rate log gabor filter can be preferred.

References

1) Turk, M & Pentland, A 1991, 'Eigenfaces for recognition', Journal of cognitive neuroscience, vol. 3, no. 1, pp. 71-86.

2) Golub, GH & Van Loan, CF 2012, Matrix computations, vol. 3, JHU Press

3) Chen, S, Zhang, D & Zhou, Z-H 2004, 'Enhanced (PC) 2 A for face recognition with one training image per person', Pattern Recognition Letters, vol. 25, no. 10, pp. 1173-1181.

4) Yin, H, Fu, P &Meng, S 2006, 'Sampled FLDA for face recognition with single training image per person', Neurocomputing, vol. 69, no. 16, pp. 2443-2445.

5) Li, J & Pan, J-S 2007, 'A novel pose and illumination robust face recognition with a single training image per person algorithm', Chinese Optics Letters, vol. 6, no. 4, pp. 255-257.

6)Gao, Q-x, Zhang, L & Zhang, D 2008, 'Face recognition using FLDA with single training image per person', Applied Mathematics and Computation, vol. 205, no. 2, pp. 726-734.

7) http://vision.ucsd.edu/content/yale-face-database

8) Koç, M &Barkana, A 2011, 'A new solution to one sample problem in face recognition using FLDA', Applied Mathematics and Computation, vol. 217, no. 24, pp. 10368-10376.

9)http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html