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Face Recognition Using Pca

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Abstract : *Security And Authentication Of A Person Is A Crucial Part Of Any Industry. There Are Many Techniques Used For This Purpose. One Of Them Is Face Recognition. Face Is The Most Common Biometric Used By Humans. It Is A Complex Multidimensional Structure And Needs Good Computing Techniques For Recognition. In This Paper We Treats Face Recognition As A Two-Dimensional Recognition Problem By Converting The Colored Image Into Greyscale Image. In This Paper We Have Done The Face Recognition By Using Principal Component Analysis (Pca). The System Consists Of A Database Of A Set Of Facial Patterns For Each Individual. Face Images Are Projected Onto A Face Space That Encodes Best Variation Among Known Face Images. The Face Space Is Defined By Eigenface Which Are Eigenvectors Of The Set Of Faces, Which May Not Correspond To General Facial Features Such As Eyes, Nose, And Lips. The Eigenface Approach Uses The Pca For Recognition Of The Images. The System Performs By Projecting Pre Extracted Face Image Onto A Set Of Face Space That Represents Significant Variations Among Known Face Images. The Characteristic Features Called 'Eigenfaces' Are Extracted From The Stored Images Using Which The System Is Trained For Subsequent Recognition Of New Images. Experiment Result For 145 Face Images Of 29 Persons Of Varying Illumination And Posture Show 80 Percent Of Successful Recognition Of Test Images.*

Keywords – *Eigenface, Eigenvalue, Eigenvectors ,Face Recognition, Pca.*

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I. INTRODUCTION

In Recent Years, Face Recognition Has Attracted Much Attention And Its Research Has Rapidly Expanded By Not Only Engineers But Also Neuroscientists, Since It Has Many Potential Applications In Computer Vision Communication And Automatic Access Control System. Especially, Face Detection Is Important Part Of Face Recognition As The First Step Of Automatic Face Recognition. However, Face Detection Is Not Straight Forward Because It Has Lots Of Variations Of Image Appearance, Such As Pose Variation (Front, Non-Front), Image Orientation, Illuminating Condition And Facial Expression. Face Recognition Is Substantially Different From Classical Pattern Recognition Problems, Such As Object Recognition. The Shapes Of The Objects Are Usually Different In An Object Recognition Task, While In Face Recognition One Always Identifies Objects With The Same Basic Shape. This Is Of Utmost Difficulty For A Face Recognition System When One Tries To Discriminate Faces All Of Which Have The Same Shape With Minor Texture Differences. The Face Recognition Therefore Depends Heavily On The Particular Choice Of Face Representation. The Aim Of Feature Selection In Face Representation Method Is To Suppress The Variations Of Face Images And Simultaneously Provide Enhanced Discriminatory Power. It Has Many Image Representations Proposed For Face Recognition Such As Eigenface Methods. The Goal Of The Eigenface Method Is To Linearly Projecting The Image Space To A Feature Space Of Lower Dimensionality. One Can Reconstruct A Face-Like Image By Using Only A Few Eigenvectors Which Correspond To The Largest Eigenvalues. Eigenface Is An Optimal Reconstruction Method In The Sense Of Minimum Mean Square Error, Which Projects The Image On The Directions That Maximize The Total Scatter Across All Classes Of Face Images. This Means That The Eigenface Is Not The Optimal Method In The Sense Of Discrimination Ability, Which Depends On The Separation Between Different Classes Rather Than The Spread Of All Classes.

Face Detection Is Defined As The Process Of Extracting Faces From Scenes. So, The System Positively Identifies A Certain Image Region As A Face. This Procedure Has Many Applications Like Face Tracking, Pose Estimation Or Compression. The Next Step -Feature Extraction- Involves Obtaining Relevant Facial Features From The Data. These Features Could Be Certain Face Regions, Variations, Angles Or Measures, Which Can Be Human Relevant (E.G. Eyes Spacing) Or Not. This Phase Has Other Applications Like Facial Feature Tracking Or Emotion Recognition. Finally, The System Does Recognize The Face.

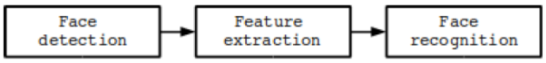

Fig 1: A Face Recognition System

II. Literature Survey

2.1 Principal Component Analysis

One Of The Most Used And Cited Statistical Method Is The Principal Component Analysis (Pca) [1]. It Is A Mathematical Procedure That Performs A Dimensionality Reduction By Extracting The Principal Components Of The Multi-Dimensional Data. The First Principal Component Is The Linear Combination Of The Original Dimensions That Has The Highest Variability. The N-Th Principal Component Is The Linear Combination With The Maximum Variability, Being Orthogonal To The N-1 First Principal Components. The Idea Of Pca Is Illustrated In Figure 1. The Greatest Variance Of Any Projection Of The Data Lies In The First Coordinate. The N-Th Coordinate Will Be The Direction Of The N-Th Maximum Variance - The N-Th Principal Component. Usually The Mean X Is Extracted From The Data, So That Pca Is Equivalent To Karhunen-Loeve Transform (Klt). So, Let Xnxm Be The The Data Matrix Where X1, ...,Xm Are The Image Vectors (Vector Columns) And N Is The Number Of Pixels Per Image. The Klt Basis Is Obtained By Solving The Eigenvalue Problem

$$C_x = \Phi\Lambda\Phi^T$$

Wherecx Is The Covariance Matrix Of The Data

$$C_x = \frac{1}{m}\sum_{i=1}^{m} x_i x_i^T$$

$$\Phi = [\emptyset_1, \dots \dots, \emptyset_{n]}$$

Is The Eigenvector Matrix Of Cx. Λ Is A Diagonal Matrix, The Eigenvalues Λ1,..., Λn Of Cx Are Located On Its Main Diagonal. Λi Is The Variance Of The Data Projected On Φi.

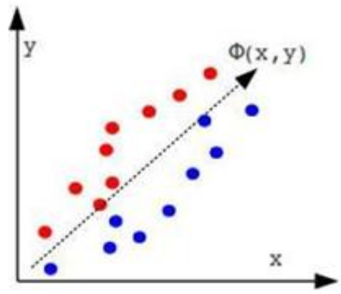

Fig 2: Pca, X And U Are The Original Basis, Φ Is The First Principal Component.

2.2 Discrete Cosine Transform

The Discrete Cosine Transform [7] Dct-Ii Standard (Often Called Simply Dct) Expresses A Sequence Of Data Points In Terms Of A Sum Of Cosine Functions Oscillating At Different Frequencies. It Has Strong Energy Compaction Properties. Therefore, It Can Be Used To Transform Images, Compacting The Variations, Allowing An Effective Dimensionality Reduction. They Have Been Widely Used For Data Compression. The Dct Is Based On The Fourier Discrete Transform, But Using Only Real Numbers. When A Dct Is Performed Over An Image, The Energy Is Compacted In The Upper-Left Corner. An Example Can Be Found In Image 1.2. The Face Has Been Taken From The Orl Database, And A Dct Performed Over It. Let B Be The Dct Of An Input Image An X M:

$$B_{pq} = \alpha_p \alpha_q \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} A_{mn} \cos\frac{\pi(2m+1)p}{2M} \cos\frac{\pi(2m+1)q}{2M}$$

$$\alpha_p = \begin{cases} 1/\sqrt{M}, p = 0 \\ \sqrt{2/M}, 1 \le p \le M-1 \end{cases} \quad \alpha_q = \begin{cases} 1/\sqrt{N}, q = 0 \\ \sqrt{2/N}, 1 \le q \le N-1 \end{cases}$$

Where M Is The Row Size And N Is The Column Size Of A. We Can Truncate The Matrix B, Retaining The Upper-Left Area, Which Has The Most Information, Reducing The Dimensionality Of The Problem.

Fig 2.1: Face Image And Its Dct

2.3 Linear Discriminant Analysis

Lda Is Widely Used To Find Linear Combinations Of Features While Preserving Class Separability. Unlike Pca, Lda Tries To Model The Differences Between Classes. Classic Lda Is Designed To Take Into Account Only Two Classes. Specifically, It Requires Data Points For Different Classes To Be Far From Each Other, While Points From The Same Class Are Close. Consequently, Lda Obtains Differenced Projection Vectors For Each Class. Multi-Class Lda Algorithms Which Can Manage More Than Two Classes Are More Used. Suppose We Have M Samples X1,...,Xm Belonging To C Classes; Each Class Has Mk Elements. We Assume That The Mean Has Been Extracted From The Samples, As In Pca. The Objective Function Of The Lda Can Be Defined As

$$a_{opt} = argmax \frac{a^T s_b a}{a^T s_t a}$$

$$S_b = \sum_{k=1}^{c} m_k \mu^{(k)} (\mu^{(k)})^T = \sum_{k=1}^{c} \left(\frac{1}{m_k} \left(\sum_{i=1}^{m_k} x_i^{(k)} \right) \right) \left(\frac{1}{l_k} \left(\sum_{i=1}^{m_k} x_i^{(k)} \right) \right)^T = XW_{mxm} X^T$$

$$S_t = \sum_{i=1}^{m} x_i (x_i)^T = XX^T$$

Where XW_{mxm} Is A Diagonal Matrix Defined As

$$W_{mxm} = \begin{bmatrix} W^1 & 0 & \dots & 0 \\ 0 & W^2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & W^c \end{bmatrix}$$

AndW^kIs $m_k \times m_k$ Matrix

$$W^k = \begin{bmatrix} \frac{1}{m_k} & \frac{1}{m_k} & \dots & \frac{1}{m_k} \\ \frac{1}{m_k} & \frac{1}{m_k} & \dots & \frac{1}{m_k} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{m_k} & \frac{1}{m_k} & \dots & \frac{1}{m_k} \end{bmatrix}$$

Finally, We Can Write The Eigen Problem:

$$S_b a = \lambda S_t a \rightarrow S_t^{-1} S_b a = \lambda a \rightarrow XW_{\iota x \iota} X^T (XX^T)^{-1} a = \lambda a$$

The Solution Of This Eigen Problem Provides The Eigenvectors; The Embedding Is Done Like The Pca Algorithm Does.

2.4 Locality Preserving Projections

The Locality Preserving Projections (Lpp) Was Introduced By He And Niyogi [8]. It's An Alternative To Pca, Designed To Preserve Locality Structure. Pattern Recognition Algorithms Usually Make A Search For The Nearest Pattern Or Neighbours. Therefore, The Locality Preserving Quality Of Lpp Can Quicken The Recognition.

Let M Be The Number Of Points That We Want To Map. In Our Case, Those Points Correspond To Images. The Lpp Algorithm Has Four Steps:

I. Constructing The Adjacency Map: A Graph G With M Nodes Is Built Using, For Example, K-Nn Algorithm. .Choosing The Weights: Being Wija Weight Matrix, We Can Build It Using A Heat Kernel Of Parameter T -If Nodes I And J Are Connected, Put

$$W_{ij} = e^{-\frac{\|x_i - x_j\|^2}{t}}$$

Ii. Solving The Eigenproblem. D Is A Diagonal Matrix Where It's Elements Are Defined As Dii = Σjωij , And L=D-W Is The Laplacian Matrix. The Following Eigen Problem Must Be Solved:

$$\lambda a = XDX^T \left(XLX^T\right)^{-1}$$

i. The Embedding Process And The Pca's Embedding Process Are Analogous.

2.5 Gabor Wavelet

Neurophysiological Evidence From The Visual Cortex Of Mammalian Brains Suggests That Simple Cells In The Visual Cortex Can Be Viewed As A Family Of Self-Similar 2d Gabor Wavelets. The Gabor Functions Proposed By Daugman [9] Are Local Spatial Bandpass Filters That Achieve The Theoretical Limit For Conjoint Resolution Of Information In The 2d Spatial And 2d Fourier Domains. Daugman Generalized The Gabor Function To The Following 2d Form:

$$\Psi_i(\vec{x}) = \frac{\|\vec{k_i}\|^2}{\sigma^2} e^{\frac{\|\vec{k_i}\|^2 \|\vec{x_i}\|^2}{2\sigma^2}} \left[e^{j\vec{k_i}\vec{x}} - e^{-\frac{\sigma^2}{2}}\right]$$

Each Ψ_i Is A Plane Wave Characterized By The Vector k_i Enveloped By A Gaussian Function, Where Σ Is The Standard Deviation Of This Gaussian. The Centre Frequency Of *I*-Th Filter Is Given By The Characteristic Wave Vector,

$$\vec{k_i} = \begin{pmatrix} k_{ix} \\ k_{iy} \end{pmatrix} = \begin{pmatrix} k_v \cos\theta_\alpha \\ k_v \sin\theta_\alpha \end{pmatrix}; k_v = \pi 2^{-\frac{v+2}{2}}; \theta_\alpha = \alpha\frac{\pi}{8}$$

Where The Scale And Orientation Is Given By (k_v, θ_α), Being V The Spatial Frequency Number And A The Orientation. An Image Is Represented By The Gabor Wavelet Transform In Four Dimensions, Two Are The Spatial Dimensions, And The Other Two Represent Spatial Frequency Structure And Spatial Relations Or Orientation. So, Processing The Face Image With Gabor Filters With 5 Spatial Frequency (V = 0, .., 4) And 8 Orientation (A = 0, .., 7) Captures The Whole Frequency Spectrum - See Image.1.3. So, We Have 40 Wavelets. The Amplitude Of Gabor Filters Are Used For Recognition. Once The Transformation Has Been Performed, Different Techniques Can Be Applied To Extract The Relevant Features, Like High-Energized Points Comparisons.

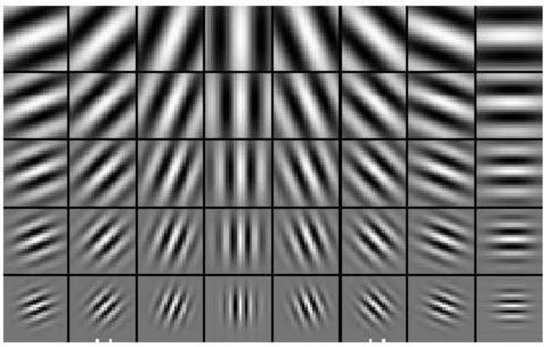

Fig 2.2: Gabor Filters

2.6 Independent Component Analysis

Independent Component Analysis Aims To Transform The Data As Linear Combinations Of Statistically Independent Data Points. Therefore, Its Goal Is To Provide An Independent Rather That Uncorrelated Image Representation. Ica Is An Alternative To Pca Which Provides A More Powerful Data Representation [10]. It's A Discriminant Analysis Criterion, Which Can Be Used To Enhance Pca.

The Ica Algorithm Is Performed As Follows. Let Cx Be The Covariance Matrix Of An Image Sample X. The Ica Of X Factorizes The Covariance Matrix Cx Into The Following Form: Cx = Fδft Where Δ Is Diagonal Real Positive And F Transforms The Original Data Into Z (X = Fz). The Components Of Z Will Be The Most Independent Possible. To Derive The Ica Transformation F,

$$X = \Phi \Lambda^{\frac{1}{2}} U$$

Where X And Λ Are Derived Solving The Following Eigen Problem:

$$c_x = \Phi \Lambda \Phi^T$$

Then, There Are Rotation Operations Which Derive Independent Components Minimizing Mutual Information. Finally, Normalization Is Carried Out.

2.7 Kernel Pca

The Use Of Kernel Functions For Performing Nonlinear Pca Was Introduced By Scholkopf Et Al [11]. Its Basic Methodology Is To Apply A Non-Linear Mapping To The Input (Ψ(X) :R^n! R^l) And Then Solve A Linear Pca In The Resulting Feature Subspace. The Mapping Of Ψ(X) Is Made Implicitly Using Kernel Functions

$$k(x_i, x_j) = \left(\Psi(x_i) . \Psi(x_j)\right)$$

Where N The Input Space Correspond To Dot- Products In The Higher Dimensional Feature Space. Assuming That The Projection Of The Data Has Been Centered, The Covariance Is Given By Cx =<$\Psi(x_i) . \Psi(x_j)^T$>, With The Resulting Eigen Problem:

$$\lambda V = C_x V$$

Where There Must Exist Some Coefficients $\Omega_i$so That

$$V = \sum_{i=1}^{M} \omega_i \Psi(x_i)$$

The Operations Performed In Lead To An Equivalent Eigen Problem:

$$M\lambda\omega = k\omega$$

The Kernel Matrix K Is Then Diagonalized By Pca. This Leads To The Conclusion [98] That The N-Th Principal Component Y_n Of X Is Given By

$$y_n = V_n . \Psi(x) = \sum_{i-1}^{M} \omega_i^n k(x, x_i)$$

Wherev_n Is The N-Th Eigenvector Of The Feature Space Defined By .

The Selection Of An Optimal Kernel Is Another Engineering Problem. Typical Kernels Include Gussians

$$k(x, y) = exp\left(-\frac{\|x - y\|^2}{2\sigma^2}\right)$$

Polynomial Kernels

$$k(x, y) = (x . y + 1)^d$$

Or Neural Network Type Kernels

$$k(x, y) = \tanh\left((x . y) + b\right)$$

2.8 Other Methods

Other Algorithms Are Worth Mentioning. For Example, Genetic Algorithms Have Been Used, And Proved More Accurate (But More Resource-Consuming) Than Pca Or Lda[12]. Other Successful Statistic Tools Include Bayesian Networks, Bi-Dimensional Regression And Ensemble-Based And Other Boosting Methods.

2.9 Neural Network Approach

Artificial Neural Networks Are A Popular Tool In Face Recognition. They Have Been Used In Pattern Recognition And Classification. Kohonen Was The First To Demonstrate That A Neuron Network Could Be Used To Recognize Aligned And Normalized Faces. Many Different Methods Based On Neural Network Have Been Proposed Since Then. Some Of These Methods Use Neural Networks Just For Classification. One Approach Is To Use Decision-Based Neural Networks, Which Classifies Pre-Processed And Sub Sampled Face Images. There Are Methods Which Perform Feature Extraction Using Neural Networks. For Example, Intratoret. Al Proposed A Hybrid Or Semi-Supervised Method. They Combined Unsupervised Methods For Extracting Features And Supervised Methods For Finding Features Able To Reduce Classification Error. They Used Feed-Forward Neural Networks (Ffnn) For Classification. They Also Tested Their Algorithm Using Additional Bias Constraints, Obtaining Better Results. They Also Demonstrated That They Could Decrease The Error Rate Training Several Neural Networks And Averaging Over Their Outputs, Although It Is More Time-Consuming That The Simple Method. Lawrence Et. Al Used Self-Organizing Map Neural Network And Convolutional Networks. Self-Organizing Maps (Som) Are Used To Project The Data In A Lower Dimensional

Space And A Convolutional Neural Network (Cnn) For Partial Translation And Deformation Invariance. Their Method Is Evaluated, By Substituting The Som With Pca And The Cnn With A Multi-Layer Perception (Mlp) And Comparing The Results. They Conclude That A Convolutional Network Is Preferable Over A Mpl Without Previous Knowledge Incorporation. The Som Seems To Be Computationally Costly And Can Be Substituted By A Pca Without Loss Of Accuracy. Overall, Ffnn And Cnn Classification Methods Are Not Optimal In Terms Of Computational Time And Complexity. Their Classification Performance Is Bounded Above By That Of The Eigenface But Is More Costly To Implement In Practice. Zhang And Fulcher Presented And Artificial Neural Network Group-Based Adaptive Tolerance (Gat) Tree Model For Translation-Invariant Face Recognition In 1996. Their Algorithm Was Developed With The Idea Of Implementing It In An Airport Surveillance System. The Algorithm's Inputs Were Passport Photographs. This Method Builds A Binary Tree Whose Nodes Are Neural Network Group-Based Nodes. So, Each Node Is A Complex Classifier, Being A Mlp The Basic Neural Network For Each Group-Based Node. Other Authors Used Probabilistic Decision Based Neural Networks (Pdbnn). Lin Et Al. Developed A Face Detection And Recognition Algorithm Using This Kind Of Network. They Applied It To Face Detection, Feature Extraction And Classification. This Network Deployed One Sub-Net For Each Class, Approximating The Decision Region Of Each Class Locally. The Inclusion Of Probability Constraints Lowered False Acceptance And False Rejection Rates.

2.10 Neural Networks With Gabor Filters

Bhuiyan Et Al. Proposed In 2007 A Neural Network Method Combined With Gabor Filter. Their Algorithm Achieves Face Recognition By Implementing A Multilayer Perceptron With Back-Propagation Algorithm. Firstly, There Is A Pre-Processing Step. Every Image Is Normalized In Terms Of Contrast And Illumination. Noise Is Reduce By A "Fuzzily Skewed" Filter. It Works By Applying Fuzzy Membership To The Neighbor Pixels Of The Target Pixel. It Uses The Median Value As The 1 Value Membership, And Reduces The Extreme Values, Taking Advantage From Median Filter And Average Filter. Then, Each Image Is Processed Through A Gabor Filter. The Filter Is Represented As A Complex Sinusoidal Signal Modulated By A Gaussian Kernel Function. The Gabor Filter Has Five Orientation Parameters And Three Spatial Frequencies, So There Are 15 Gabor Wavelets. The Architecture Of The Neural Network Is Illustrated In Figure 1.4. To Each Face Image, The Outputs Are 15 Gabor-Images Which Record The Variations Measured By The Gabor Filters. The First Layer Receives The Gabor Features. The Number Of Nodes Is Equal To The Dimension Of The Feature Vector Containing The Gabor Features. The Output Of The Network Is The Number Of Images The System Must Recognize. The Training Of The Network, The Backpropagation Algorithm, Follows This Procedure:

1. Initialization Of The Weights And Threshold Values.
2. Iterative Process Until Termination Condition Is Fulfilled:

(A) Activate, Applying Input And Desired Outputs. Calculate Actual Outputs Of Neurons In Hidden And Output Layers, Using Sigmoid Activation Function.
(B) Update Weights, Propagating Backwards The Errors.
(C) Increase Iteration Value

Although The Algorithms Main Purpose Is To Face Illumination Variations, It Shows A Useful Neural Network Application For Face Recognition. It Could Be Useful With Some Improvements In Order To Deal With Pose And Occlusion Problems.

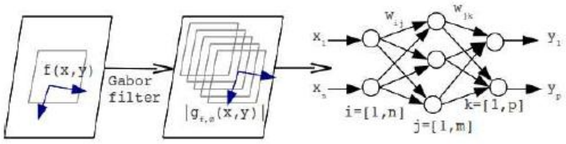

Fig 2.3: Neural Networks With Gabor Filters

III. PCA

Principal Component Analysis (Pca) Was Invented In 1901 By Karl Pearson. It Is A Linear Transformation Based On Statistical Technique. It Is Used To Decrease The Dimension Of The Data Or To Reduce The Correlation Between Them. It Is A Way Of Identifying Patterns Present In Data, And Expressing The Data In Such A Way That Their Similarities And Differences Are Highlight. Since Patterns Present In Data Can Be Hard To Find In Data Of High Dimension, Where It Cannot Be Represented Graphically, Pca Is A Powerful Tool For Face Detection Which Is Multi-Dimensional. The Purpose Of Pca Is To Reduce The Large Dimension Of Data Space To A Smaller Intrinsic Dimension Of Feature Vector (Independent Variable), Which Are Used To Describe The Data Cost Effectively. The First Principal Component Is The Linear Combination Of The Original Dimension Along Which The Variance Is Maximum. The Second Principal Component Is The

Linear Combination Of The Original Dimension Along Which The Variance Is Maximum And Which Is Orthogonal To The First Principal Component. The N-Th Principal Component Is The Linear Combination With Highest Variance, Subject To Being Orthogonal To N-1 Principal Component.

3.1 Pca Theory

Principal Component Analysis In Signal Processing Can Be Described As A Transform Of A Given Set Of N Input Vectors Each Of Length K Formed In The N-Dimensional Vector $X = [X_1, X_2, \ldots ,X_n]^T$ Into A Vector Y According To Each Row Of X Have K Variables Belonging To One Input. Mx Represents The Mean Or Expectation Of All Input Variables Defined As: The Matrix A In The Above Equation Is Derived From The Covariance Matrix C_x . Rows Of The Matrix A Are The Eigen Vector Of The Covariance Matrix Arrange According To The Decreasing Order Of Their Eigen Value. The Covariance Matrix Is Given By: As X Is A N Dimensional Vector So C_x Is A Nx_n Vector Where Each Element Is Given By: Rows Of A Are Orthogonal To Each Other. We Choose The Number Of Rows To Be Present In A, Which Is Less Than Or Equal To N, And Represent The Dimension To Which We Want To Reduce Y.

3.2 Steps For Pca

Step 1: Get Image In The Training Set

Orl Is A Popular Database Called Database Of Faces. Orl Database Contain Ten Different Images Of 40 Distinct Subjects. The Images Were Taken At Different Times, Varying The Lighting, Facial Expressions (Open / Closed Eyes, Smiling / Not Smiling) And Facial Details (Glasses / No Glasses). All The Images Were Taken Against A Dark Homogeneous Background With The Subjects In An Upright, Frontal Position (With Tolerance For Some Side Movement). These Face Images Taken Between April 1992 And April 1994 At The At&T Laboratories Cambridge. This Database Is Use In Face Recognition Project By Many Student And Research Scholar.

But In Our Face Recognition Project We Will Be Using Our Own Database. In Our Own Database It Contain Five Image Each Of 29 Subjects. These Face Images Are Collected From Our Mizoram University Campus. These Images Were Taken At Different Times, Varying The Lighting, Facial Expressions And Facial Details. All The Images Were Taken Against A Dark Homogeneous Background With The Subjects In An Upright, Frontal Position (With Tolerance For Some Side Movement). The Images Are Of 196*256 Pixels And Are In The .Jpg Format.

After Getting Database Of Faces, We Should Organize The Images For Simple Computation, To Do So We Should Reshape Each Image Into A Long Column Of Pixels I.E. 2d To 1d Which Is Face Vector. After Reshape Create A Matrix Where Each Column Of Matrix Corresponds To Face Vector.

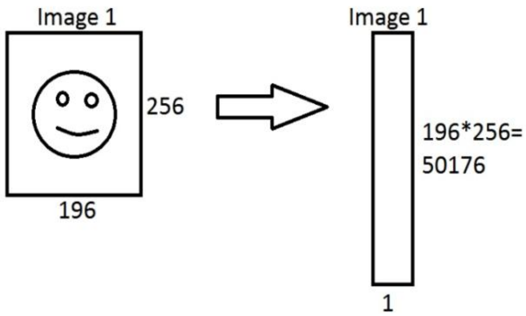

Fig 3: Reshape Of Image 2d To 1d

The Matrix In Case Of The Database We Use, It Should Have 145 Columns And 50176 Rows. The 145 Columns Correspond To The 145 Images That Exist In The Database And 50176 Correspond To The Number Of Pixels In The Image.

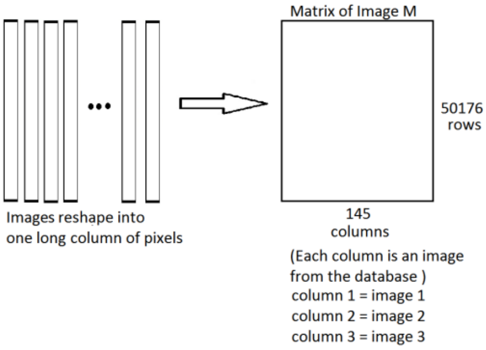

Fig 3.1: Reshape Of All Images In The Database It Matrix Of Image M.

Step 2: Normalize The Face Vectors

1. 1. Calculate The Average Face Vectors.

We Have Database Of Faces And Turn It Into Matrix Of Face Vector. To Find Average Face We Need To Add The Entire Image Together And Divide By The Total Number Of Image.

In The Case Of Matrix Database Of Face Each Column Should Be Added Together So That Final Sum Has Dimension Of 1 Column By 50176 Rows.

The Average (Mean) Face Is Obtained By $\Psi = \frac{1}{M}\sum_{i=1}^{n}\Gamma i$, Where $\Gamma_1, \Gamma_2, \Gamma_3, \ldots\ldots, \Gamma_m$ Are Face Vector.

Fig 3.2: Mean Face

2. Subtract Average Face Vector From Each Face Vector From Each Face Vector.

Here To Get The Normalize Face Vector It Need To Subtract Average Face Vector From Each Vector. The Normalization Face Vector Ids Obtain By $\Phi_i = T_i - \Psi$, Where $\Phi_i$represent How Each Of The Image In Database Is Different From The Average Face Vectors.

Step 3: Calculate The Eigenvector

To Calculate Eigenvector, First Need To Find Covariance Matrix. The Covariance Is Obtain By

$C = A.A^T$, where $A = [\Phi 1, \Phi 2, \Phi 3, \ldots.., \Phi M,]$ of $N^2 \times N^2$

Size Of Covariance Matrix C Will Be$N^2 \times N^2$.

Since

$C = A.A^T = N^2 \times M \,.\, M \times N^2 = N^2 \times N^2$

To Calculate Eigenvectors From This Covariance Matrix Will Take Tedious Task And Will Take More Computational Time.

For Simplicity Calculate Covariance Matrix

$C = A^T.A = M \times N^2.N^2 \times M = M \times M$

Resulting In $M \times M$ Matrix Reduce The Dimensional And Increasing Computational Time.

After Finding Out Covariance Matrix It Needs To Find The Eigenvalue To Get Eigenvactor.

Eigenvalue Of Covariance Matrix C Is

$eigenvalue = \det(C - \lambda I) = 0$

$where \lambda I = \begin{bmatrix} \lambda & 0 \\ 0 & \lambda \end{bmatrix}$

After Getting Eigenvalues We Can Find Eigenvector

$Eigenvector = Eigenvalue \times CovarianceMatrix$

Step 4: Chosen For Creating Eigenface
Eigenfaces Is A Set Of Eigenvectors**.** This Means That It May Be Equal Or Less Than The Eigenvector. If Corresponding Eigenvalue Is Greater Than 1, Then The Eigenvector Will Be Chosen For Creating Eigenface.

IV. EXPERIMENTAL RESULTS

Matlab 2012 Is Used For Coding. A Colored Rgb Face Image Is Converted To Gray Scale Image As Gray Scale Images Are Easier For Applying Computational Techniques In Image Processing.
A Gray Scale Face Image Is Scaled For A Particular Pixel Size As 196x256 Because Many Input Images Can Be Of Different Size Whenever We Take An Input Face For Recognition.

Training Set

Database For Different Set Of Conditions Is Maintained. Five Different Expressions For Twenty Nine Different People Thus Creating A 29x5 That Is Equal To 145 Different Set Of Face Images. Rotated Images In Left And Right Direction And Up And Down Direction Are Also Considered While Making The Training Set.

Fig 4: A Single Face Image For Five Different Expressions.

In These Experiment We Have Used The Algorithm Discussed In The Previous Chapter And Have Found Out The Principal Components.

Fig 4.1: Shows The Image Of 5 Person In Different Pose

Fig 4.2: Normalized Training Set

In The Above Figure We Have Normalized The Training Set Of 50 Different Images. From These Images We Have Find Out The Mean Image.

4.3: Mean Image Of 50 Different Images.

By Subtracting The Mean From The Normalized Training Set, We Find Out The Eigenfaces.

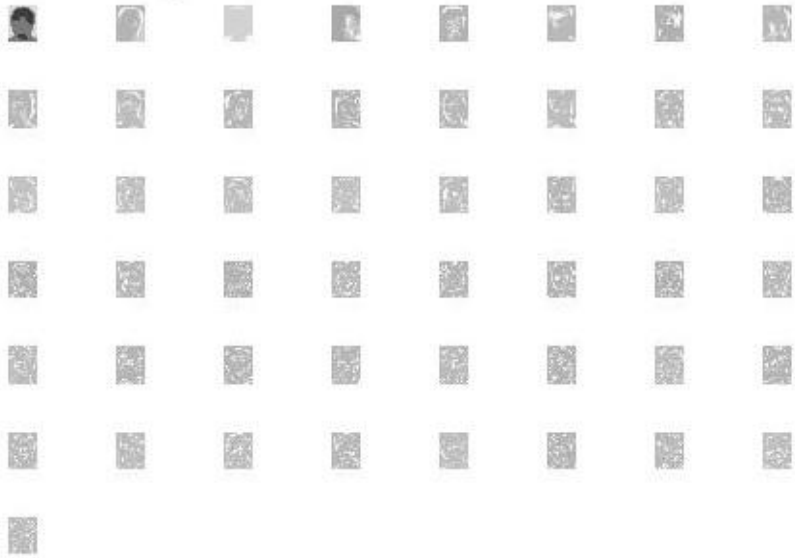

Fig 4.4: Eigenfaces

After The Eigenfaces Are Found Out, We Enter The Name Of The Images And The Extension For Calculation Of The Euclidean Distance Of The Image.

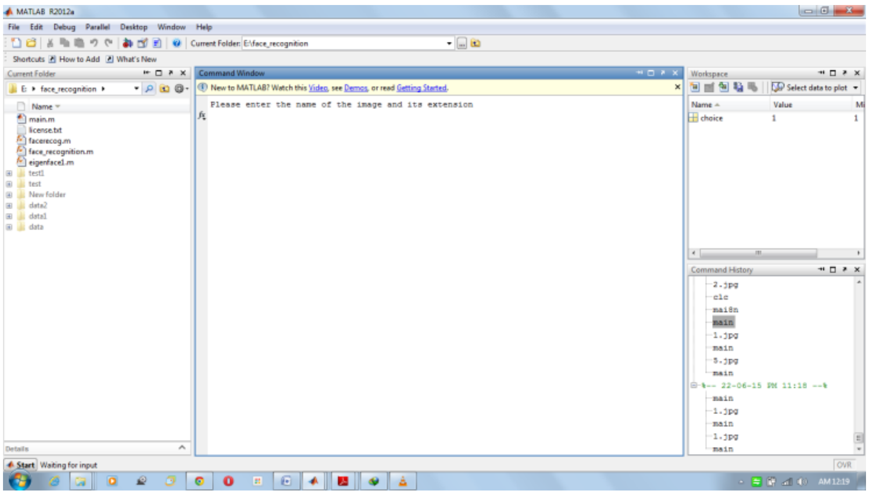

Fig 4.5: Screenshot Of The Function To Input The Image Name And Extension For Euclidean Calculation.

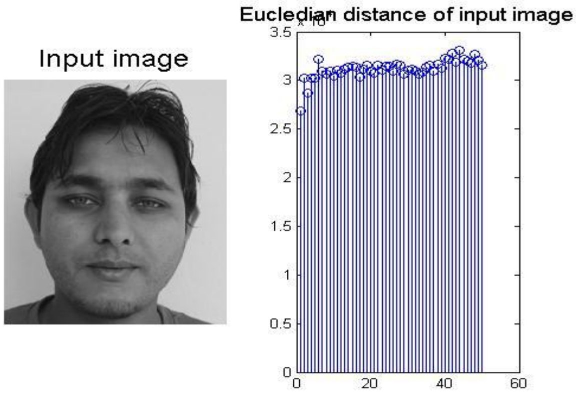

Fig 4.6: Eucledian Distance Of The Input Image

After The Euclidean Distance Is Calculated We Input The Test Image For Recognition.

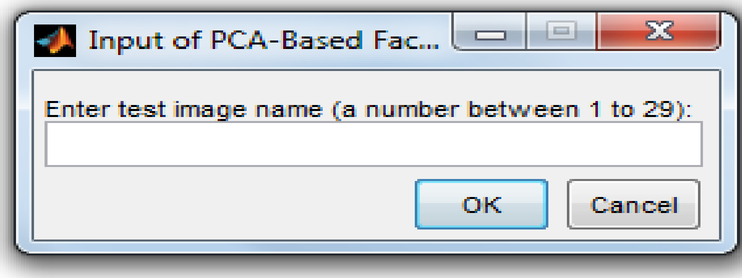

Fig 4.7: Prompt Function For Input Of Test Image

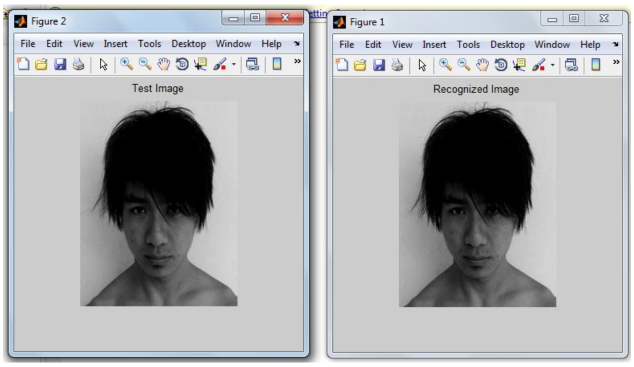

Fig 4.8: Test Image Recognition From The Database

When We Input The Name Of The Image In The Prompt Function, It Recognized The Image From The Database, Thus Showing The Test Image And The Recognized Image. Hence The Image Is Recognized.

V. Conclusion

Face Recognition System Using Principal Component Analysis. The System Successfully Recognized The Images. In Pca, It Suffers From Background, Lighting Conditions And Scale Orientation.Face Recognition Is A Both Challenging And Important Recognition Technique. Among All The Biometric Techniques, Face Recognition Approach Possesses One Great Advantage, Which Is Its User-Friendliness (Or Non-Intrusiveness). Face Recognition Is A Technology Just Reaching Sufficient Maturity For It To Experience A Rapid Growth In Its Practical Applications. Much Research Effort Around The World Is Being Applied To Expanding The Accuracy And Capabilities Of This Biometric Domain, With A Consequent Broadening Of Its Application In The Near Future. Verification Systems For Physical And Electronic Access Security Are Available Today, But The Future Holds The Promise And The Threat Of Passive Customization And Automated Surveillance Systems Enabled By Face Recognition. In This Paper, We Have Given An Introductory Survey For The Face Recognition Technology.

We Have Covered Issues Such As The Framework For Face Recognition Using Principal Component Analysis (Pca), Factors That May Affect The Performance Of The Recognizer, And Several State-Of-The-Art Face Recognition Algorithms. We Hope This Paper Can Provide The Readers A Better Understanding About Face Recognition, And We Encourage The Readers Who Are Interested In This Topic To Go To The References For More Detailed Study.

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