In traditional approach, we use PCA to do dimensionality reduction and then do LDA. Techniques based on PCA, we always called it eigenfaces. There are two phases in PCA based approaches: 1. Using PCA on training set to establish eigen space and project training set into eigen space. 2. Projecting input image into subspace and classified by different approach. In PCA+LDA separate model, the null space of Sw contains the most discriminant information when the projection of Sb is not zero in that direction. Consider an extreme case where each class has only one sample, we can maximize Sb subject to the constraint that Sw =0.

However, this paper come up with a new algorithm: maximizes the LDA criterion directly without a separate PCA step. This eliminates the possibility of losing discriminative information due to a separate PCA step. If we begin diagonalization from Sb , we need to keep Sb non-singular. It will not lose any useful information if we remove the null space from Sb .

Direct LDA Algorithm for Face Recognition

1. Remove the null space from Sb and diagonalize Sb . Do the eigen analysis of Sb and sort eigen vector in descending order of the corresponding eigenvalues. Map each eigen vector x of Sb onto W. The first step of the new algorithm has a dual pur- pose: dimensionality reduction and sub-space map- ping.

Normalize the v's and write them down side by side to get V, such that

$$V^T S_b V = \Lambda, \quad (7)$$

where $V^T V = I$, Λ is diagonal matrix sorted in de- creasing order. Discard those with eigenvalues suf- ficient close to 0 (below ϵ). Let Y be the first m columns of V, we have

$$Y^T S_b Y = D_b, \quad (8)$$

2. Diagonalize Sw

$$(Y D_b^{-\frac{1}{2}})^T S_b (Y D_b^{-\frac{1}{2}}) = Z^T S_b Z = I. \quad (9)$$

Diagonalize $Z^T S_w Z$ by eigen analysis:

$$U^T Z^T S_w Z U = D_w, \quad (10)$$

where $U^T U = I$, D_w may have $0s$ in its diagonal. Again, we can utilize Lemma 1 to compute eigenval- ues, i.e.,

$$Z^T S_w Z = Z^T \Phi_w \Phi_w^T Z = (\Phi_w^T Z)^T \Phi_w^T Z . \quad (11)$$

In fact, we can sort the diagonal ele- ments of Dw in a decreasing order and discard some eigenvectors with large eigenvalues.

3.

3. The LDA transformation is:

$$A = (ZU)^T . \quad (12)$$

Matrix A diagonalizes both the numerator and the denominator of Fisher's criterion:

$$A S_w A^T = D_w, \; A S_b A^T = I.$$

4. Finally, we can sphere the data into a more spherical shape, which is done with the transformation: $X^* \leftarrow D_w^{-\frac{1}{2}} AX.$

The new algorithm keeps the most discriminant projection direction embedded in the null space of Sw . The algorithm can take advantage of all useful information inside and outside of SW's null space. The new algorithm has unified PCA/LDA algorithm by naturally combining the PCA technique into eigen analysis of LDA.

Face Extraction : a prerequisite for face recognition. For face extraction, we use the real-time face tracking technology. It uses an adaptive skin-color model to extract what is in high likelihood a face from an image. For face extraction purposes, the system focuses on the location of the eyes, and uses particularly the distance between the eyes to establish a bounding box for the face. It was empirically determined that a satisfactory size for the bounding box is four times the distance between the eyes in height and three times the distance between the eyes in width centered around the point between the eyes.

Face Recognition :The module starts by loading database of face classified by different recognition algorithms We have currently implemented many different face recognition algorithms, such PCA , PCA + LDA , and direct LDA.