

# **Lecture 33**

## **PCA-based Face Recognition**

### **ECEN 5283 Computer Vision**

Dr. Guoliang Fan  
School of Electrical and Computer Engineering  
Oklahoma State University

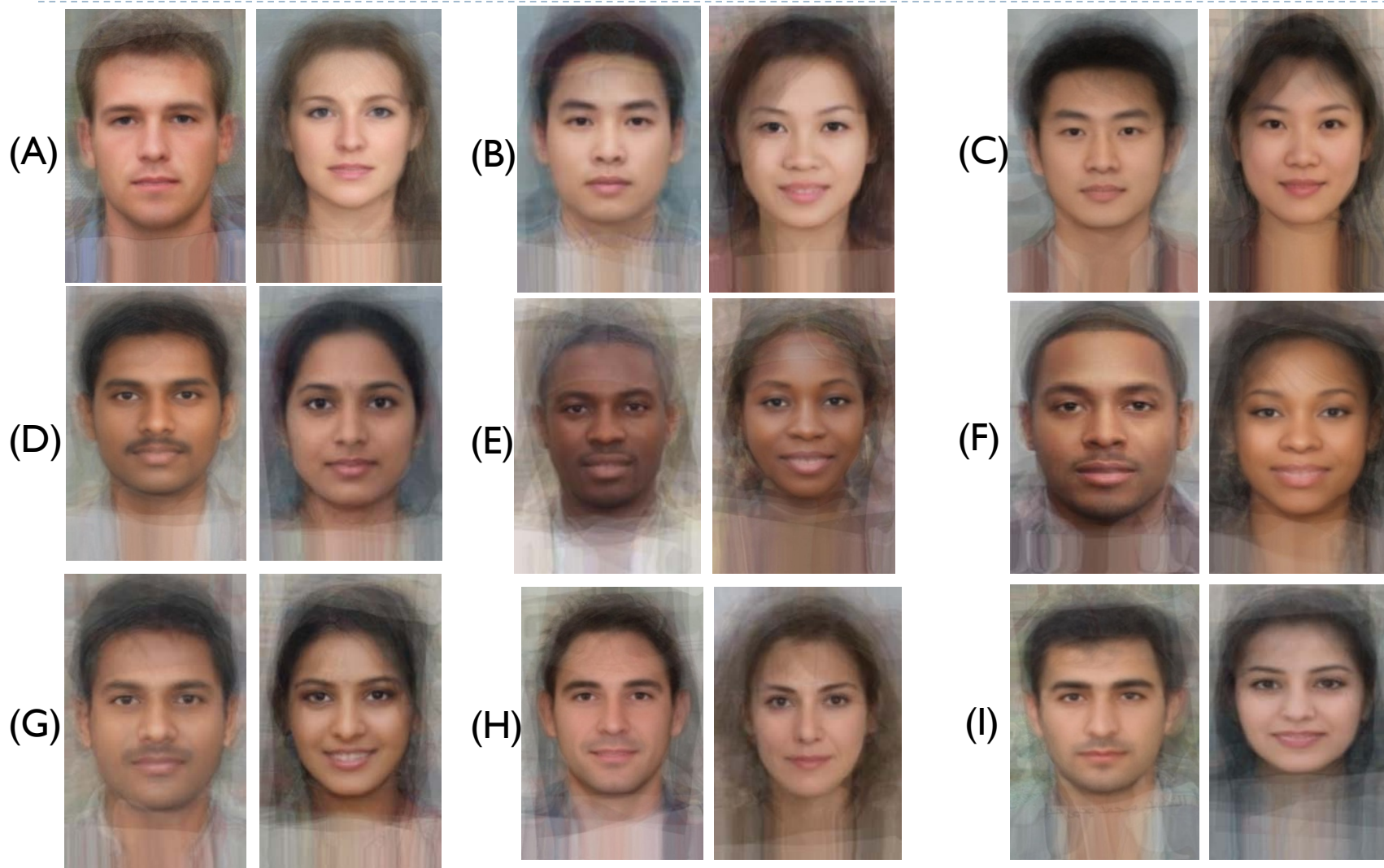


# Goals

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- ▶ To review the linear dimension reduction technique, Principal Component Analysis (PCA).
- ▶ To apply PCA for face recognition.

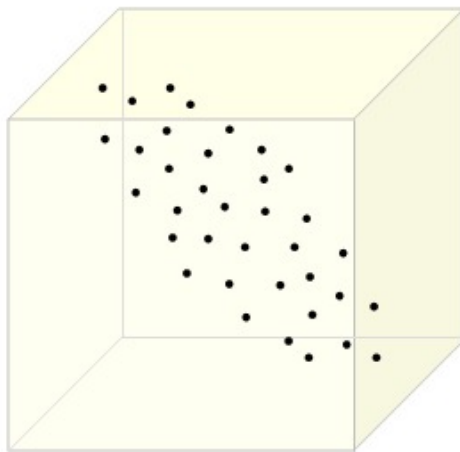
# Average Male and Female Faces from Different Races (pmsol3.wordpress.com)



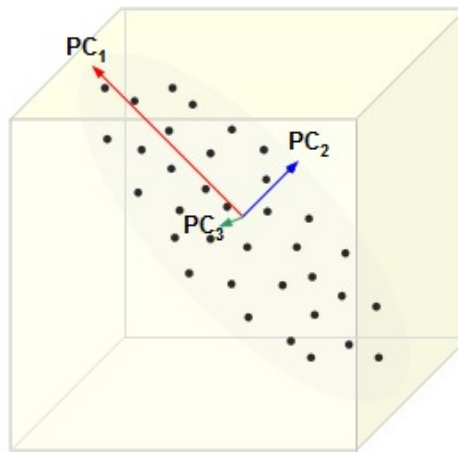
# Principal Component Analysis (PCA)



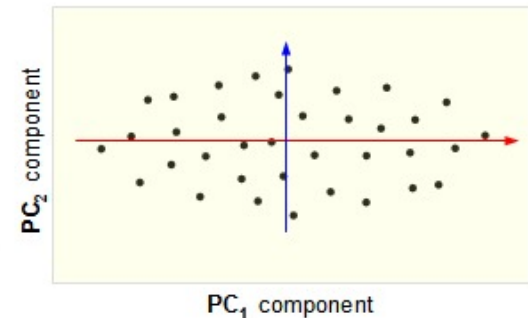
- ▶ **PCA** *provides compact data representation*
  - ▶ PCA constructs a lower dimensional **linear subspace** that “**best explains**” (in the MSE sense) the variation of data points from their mean.
  - ▶ All data will be represented in this low-dimension feature space where high-level vision tasks can be efficiently accomplished.



a



b



c

# PCA: Solution

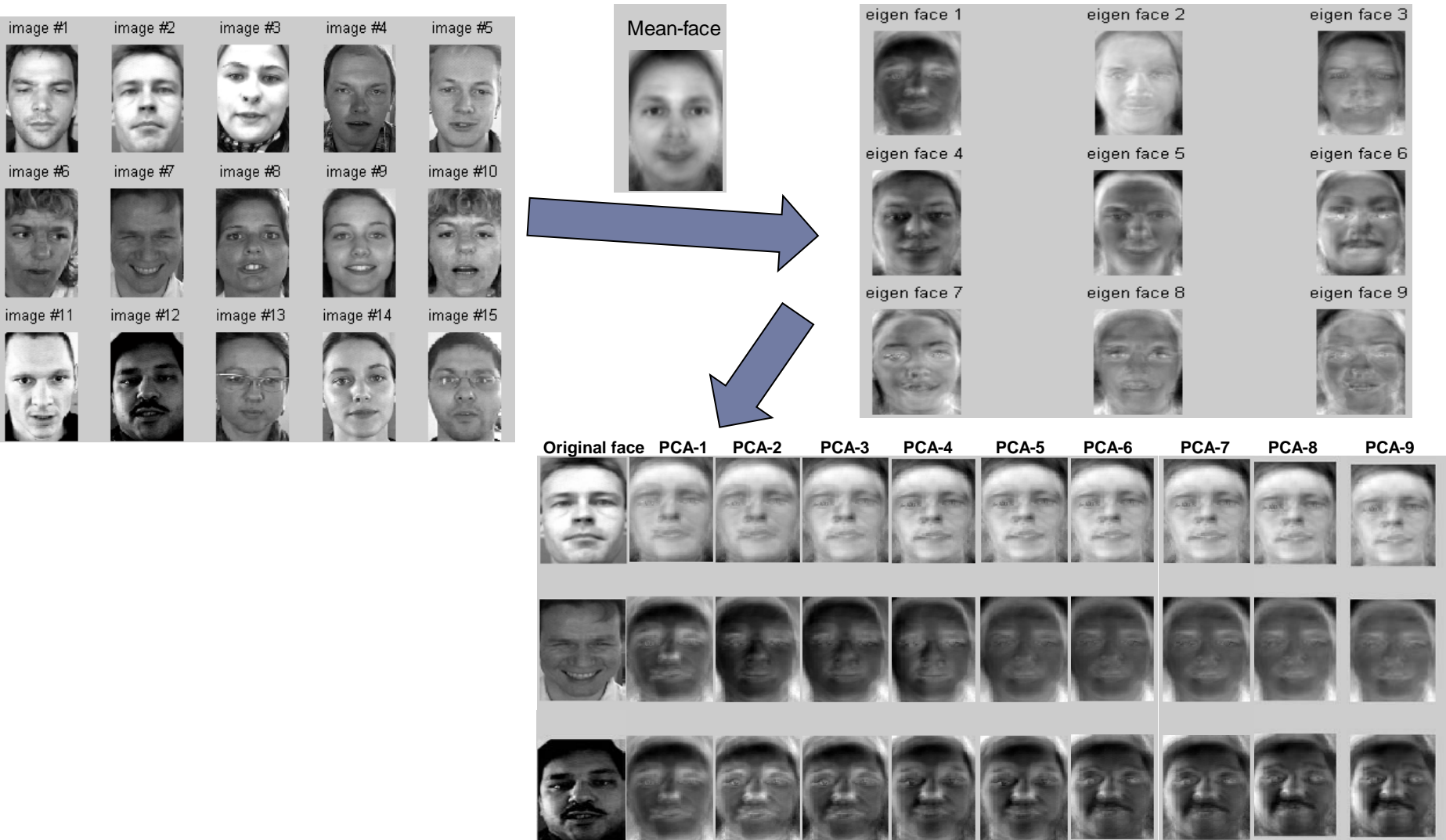
- ▶ We would like to maximize  $\mathbf{v}^T \Sigma \mathbf{v}$  subject to  $\mathbf{v}^T \mathbf{v} = 1$ .

$$\Sigma = \mathbf{Q} \begin{bmatrix} \lambda_1^2 & 0 & 0 & 0 \\ 0 & \lambda_2^2 & 0 & 0 \\ 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \lambda_q^2 \end{bmatrix} \mathbf{Q}^T \quad \text{with } 0 \leq \lambda_1^2 \leq \dots \leq \lambda_q^2 \quad \text{and } \mathbf{Q} = \begin{pmatrix} \mathbf{e}_1^T \\ \vdots \\ \mathbf{e}_q^T \end{pmatrix}$$

- ▶ This is an eigenvalue problem, and the eigenvector corresponding to the largest eigenvalue  $\mathbf{e}_q$  is the solution.
- ▶ The eigenvectors associated large eigenvalues reveals the underlying data distribution.
- ▶ The accuracy of PCA is determined by the ratio between the sum of top largest eigenvalues and that of all eigenvalues.

$$\frac{\sum_{k=p}^q \lambda_k^2}{\sum_{k=1}^q \lambda_k^2}$$

# Eigen-face for Face Recognition



# Face Recognition: Off-line Training

- ▶ Step 1: Collect a set of images of  $m$  persons, reflecting  $n$  variations in expression, pose and lighting

$$\{\mathbf{I}_j^k \mid j = 1, \dots, m, k = 1, \dots, n\};$$

- ▶ Step 2: Compute the mean  $\mu$  and eigenfaces  $\{\mathbf{u}_1, \dots, \mathbf{u}_p\}$  via PCA that construct a low-dimensional subspace  $V_p$ .
- ▶ Step 3: For the  $j$ th person in the database, calculate the corresponding representative vector in the subspace  $V_p$  spanned by the eigenfaces

$$\alpha_j^i = \frac{1}{n} \sum_{k=1}^n ((\mathbf{I}_j^k - \mu), \mathbf{u}_i) \rightarrow \mathbf{w}_j = (\alpha_j^1 \quad \alpha_j^2 \quad \dots \quad \alpha_j^p)$$

p-dimensional  
representation of  
the  $j$ th person's face

- ▶ The representative image for the  $j$ th person is  $\hat{\mathbf{I}}_j = \left( \sum_{i=1}^p \alpha_j^i \mathbf{u}_i \right) + \mu$

# Face Recognition: Online Recognition



- ▶ Step 4: Compute the projection of an new image  $\mathbf{I}_t$  on to  $V_p$ .

$$\beta_t^i = ((\mathbf{I}_t - \mu), \mathbf{u}_i) \rightarrow \mathbf{w}_t = (\beta_t^1 \quad \beta_t^2 \quad \dots \quad \beta_t^p) \rightarrow \hat{\mathbf{I}}_t = \left( \sum_{i=1}^p \beta_t^i \mathbf{u}_i \right) + \mu$$

- ▶ Step 5. If the distance  $|\hat{\mathbf{I}}_t - \mathbf{I}_t|$  is greater than a pre-set threshold, classify the image as “non-face”.
- ▶ Step 6. Otherwise, if the minimum distance  $d_k = |\mathbf{w}_t - \mathbf{w}_k|$  between the projection of the new image and the known representative is smaller than some pre-set threshold, classify the image as “person number k”

$$k = \arg_k \min d_k = \arg_k \min |\mathbf{w}_t - \mathbf{w}_k|$$

- ▶ Step 7. In the remaining case, classify the image as “unknown”.



# More discussion

Reconstructed face  
image of the given  
unknown person

Representative  
face image of  
person k

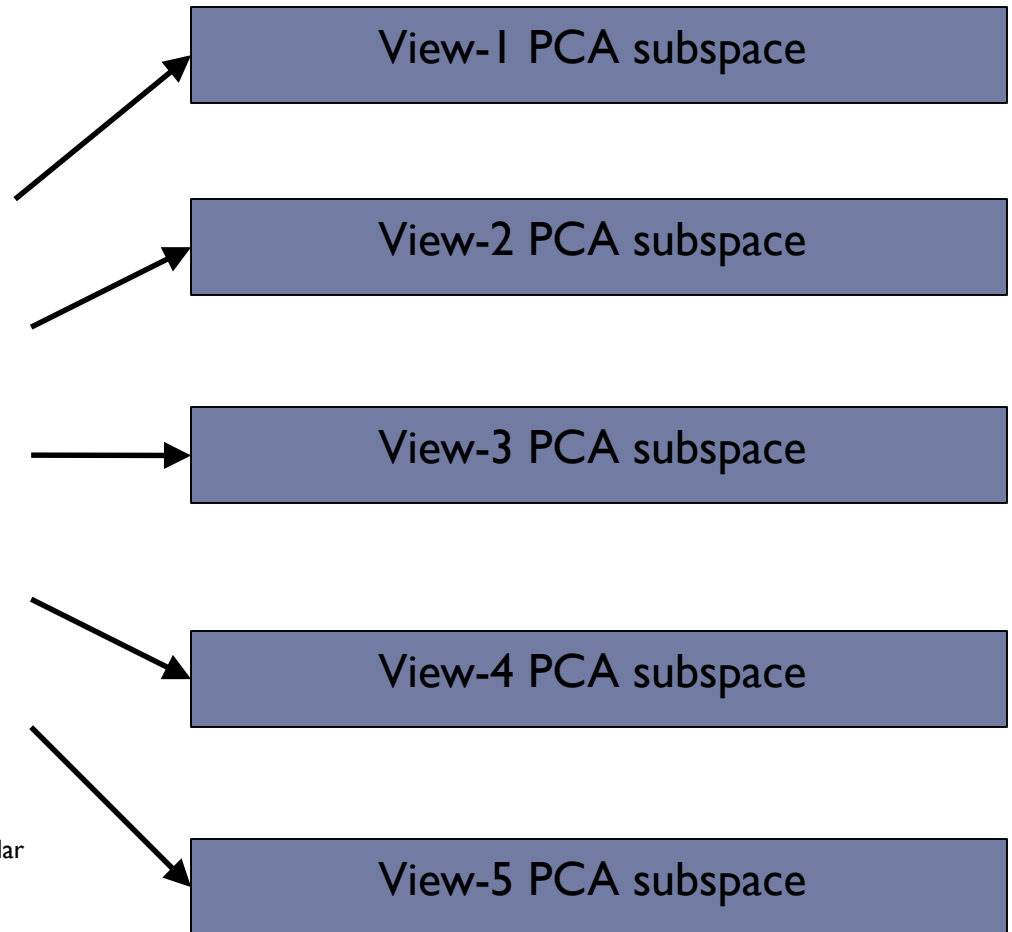
$$\begin{aligned}
 e_k &= \left| \hat{\mathbf{I}}_t - \hat{\mathbf{I}}_k \right| \\
 \hat{\mathbf{I}}_t &= \left( \sum_{i=1}^p \beta_t^i \mathbf{u}_i \right) + \boldsymbol{\mu} \rightarrow \mathbf{w}_t = (\beta_t^1 \quad \beta_t^2 \quad \dots \quad \beta_t^p) \\
 \hat{\mathbf{I}}_j &= \left( \sum_{i=1}^p \alpha_j^i \mathbf{u}_i \right) + \boldsymbol{\mu} \rightarrow \mathbf{w}_j = (\alpha_j^1 \quad \alpha_j^2 \quad \dots \quad \alpha_j^p) \\
 &= \left| \sum_{i=1}^p (\beta_t^i - \alpha_k^i) \mathbf{u}_i \right| \quad (\mathbf{u}_i, \mathbf{u}_j) = \begin{cases} 1 & i = j \\ 0 & \text{Otherwise} \end{cases} \\
 &= \left( \sum_{i=1}^p (\beta_t^i - \alpha_k^i)^2 \right)^{1/2} = \left| \mathbf{w}_k - \mathbf{w}_t \right| = d_k
 \end{aligned}$$

# Recognition by Rank

- Usually, face recognition is done by a rank. Given the top K candidates with the best match, if a face of the correct identity is included, then the recognition is a success.

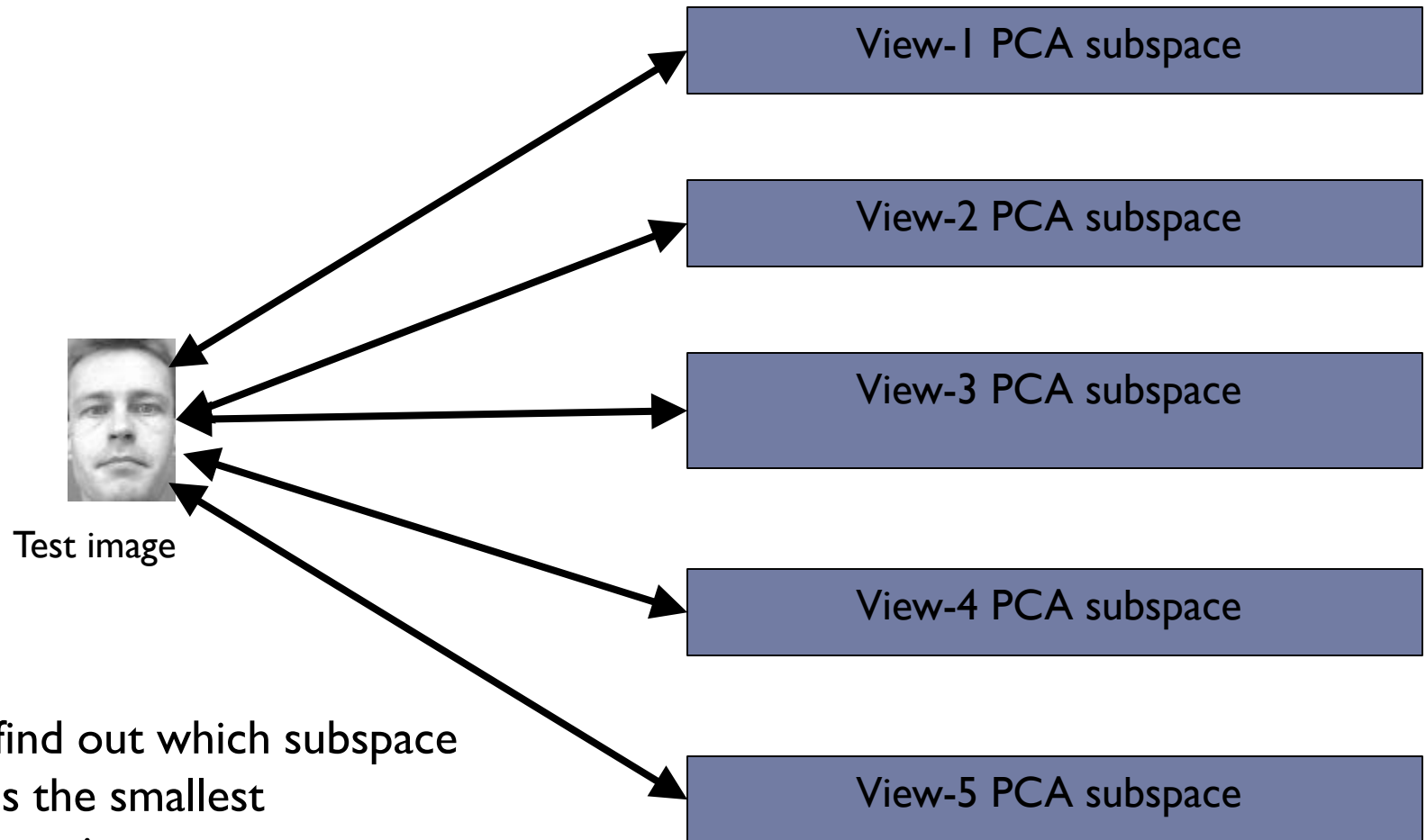


# View-based PCA



Pentland, B. Moghaddam, and T. Starner. View-based and modular eigenspaces for face recognition. In Proc. of IEEE CVPR, 1994

# How to estimate the view?



Just to find out which subspace provides the smallest reconstruction error.