

Analysis and Understanding of Various Models for Face Recognition

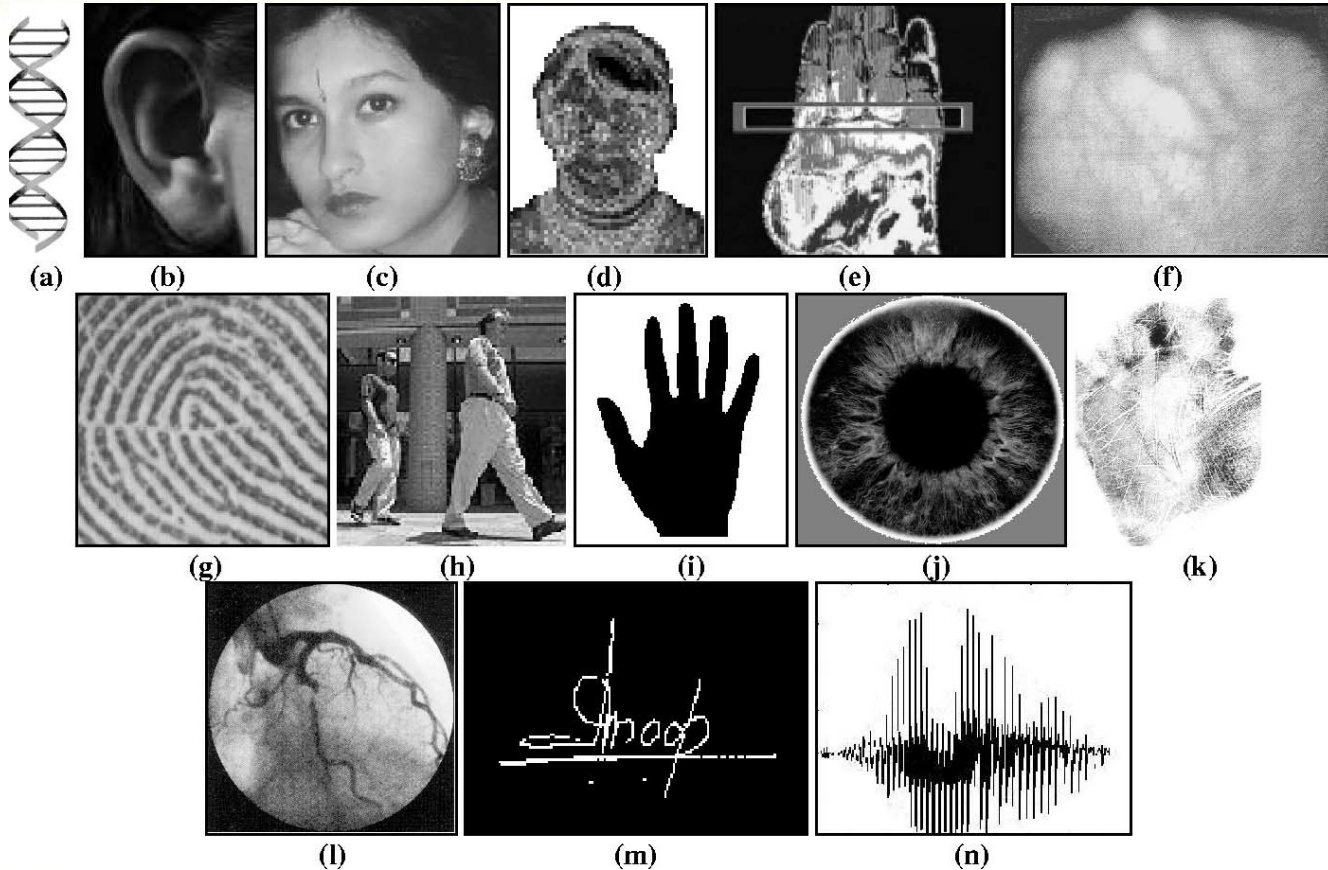
Biometrics

Biometrics are automated methods of recognizing a person based on a physiological or behavioral characteristics

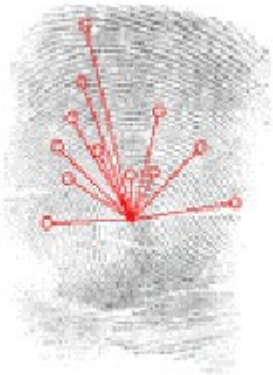
Biometrics Types

- Face
- Iris
- Speech
- Palm
- Veins
- DNA
- Skin
- Fingerprint

Types of Biometrics



Fingerprint



- Reliable
- Non Intrusive
- **Needs co-operation of the individual**



Face Recognition

- The facial recognition process involves applying a mathematical algorithm to an image and then either storing or retrieving a match for that image from a database.
- Face recognition has recently received significant attention as one of the most successful applications of image analysis and understanding, especially during the past several years.



Face Recognition

It is a Good compromise between reliability & social acceptance & balances security & privacy well.

Various Face Recognition Models

- Holistic Approach
 - Considers the whole face image
- Feature based Approach
 - Local features of face are used
- Hybrid Approach
 - Human vision – Both local feature and whole face

Eigen Faces

- Eigenfaces is one of the holistic approach used in the computer vision problem of human face recognition.
- The approach of using eigenfaces for recognition was developed by Sirovich and Kirby (1987) and used by Matthew Turk and Alex Pentland in face classification.

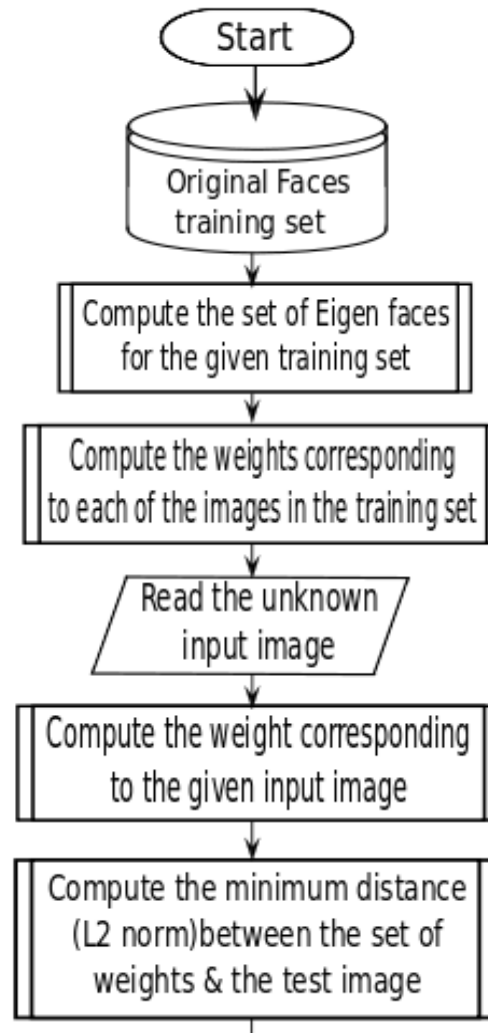
Eigen Faces

- Eigenfaces are the “standardized face ingredients” derived from the statistical analysis of many pictures of human faces
- A human face may be considered to be a combination of these “standardized faces”

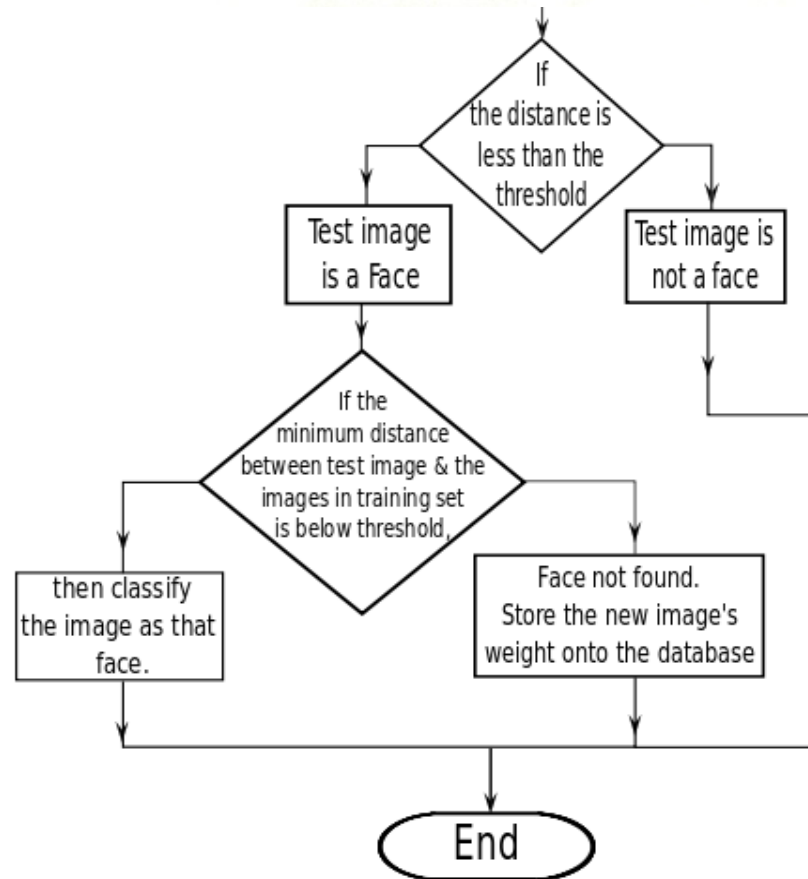
Generating Eigenfaces

- Large set of images of human faces is taken.
- The images are normalized to line up the eyes, mouths and other features.
- The eigenvectors of the covariance matrix of the face image vectors are then extracted.
- These eigenvectors are called eigenfaces.

Face recognition process using Eigen faces



Face recognition process using Eigen faces

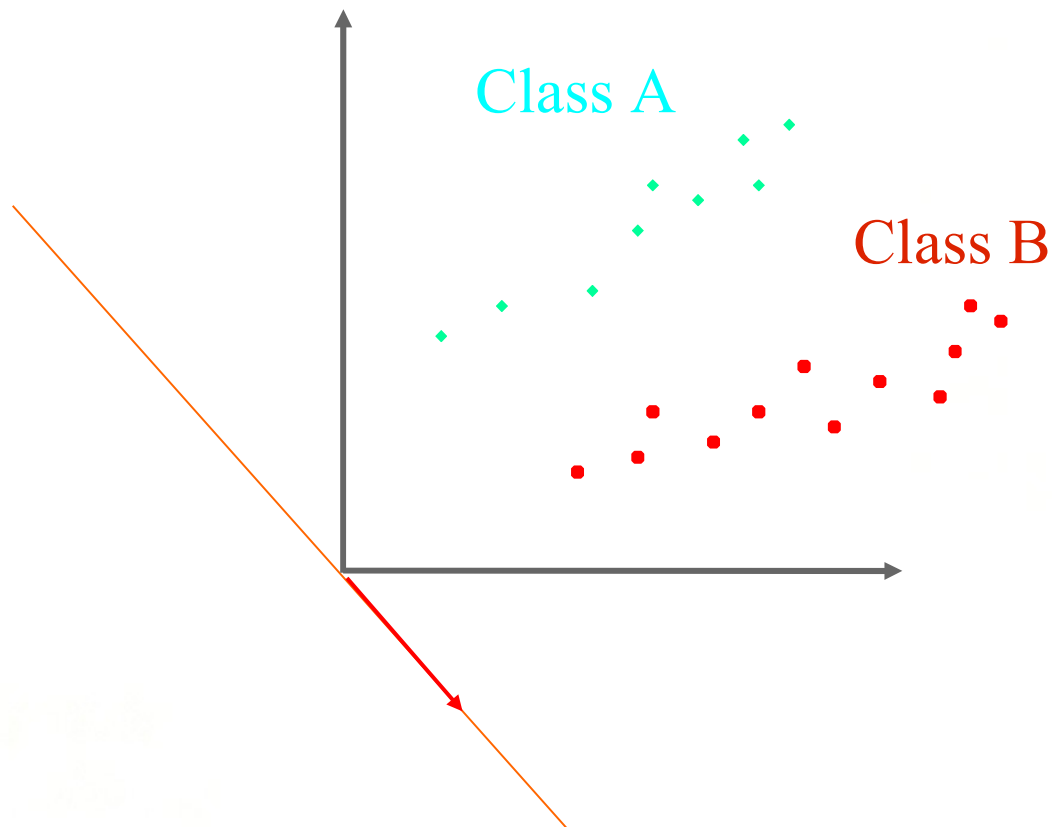


Fisher faces

Developed in 1997 by P. Belhumeur et al.
Based on Fisher's LDA Faster than
eigenfaces, in some cases. Has lower error
rates Works well even if different
illumination Works well even if different
facial express.

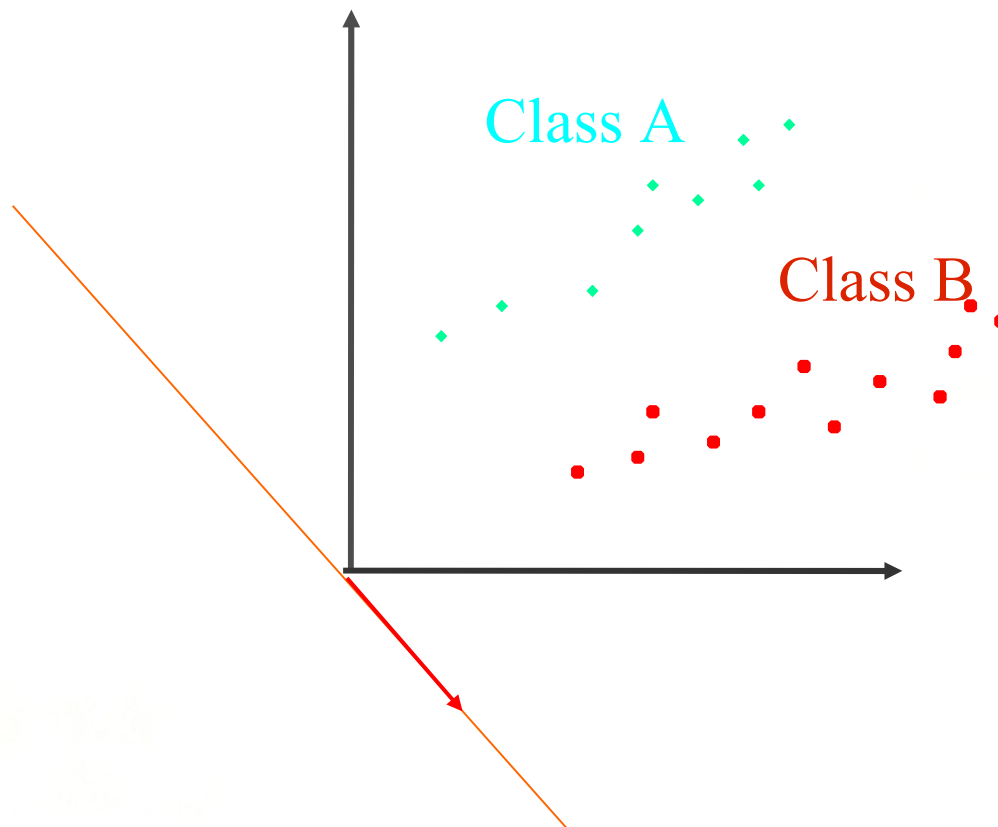
Fisherfaces

- LDA maximizes the between-class scatter
- LDA minimizes the within-class scatter



Fisherfaces

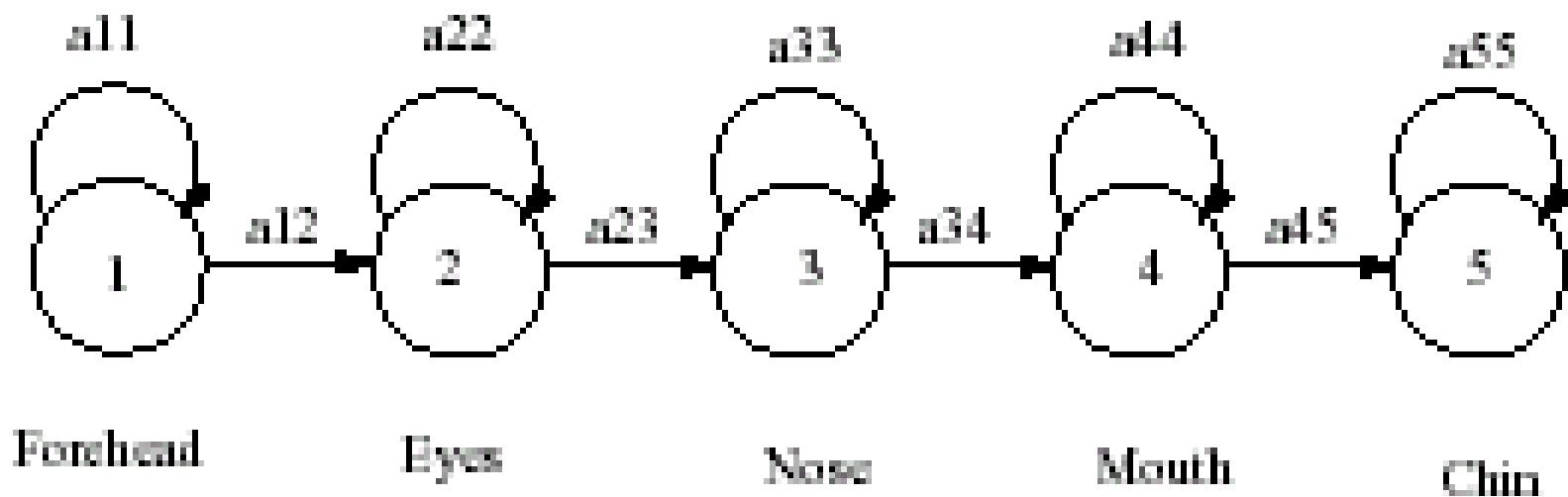
- LDA maximizes the between-class scatter
- LDA minimizes the within-class scatter



Hidden Markov Model

- HMM is a Markov chain with finite number of unobservable states. These states has a probability distribution associated with the set of observation vectors.
- Things necessary to characterize HMM are::
 - State transition probability matrix.
 - Initial state probability distribution.
 - Probability density function associated with observations for each of state.

HMM Model



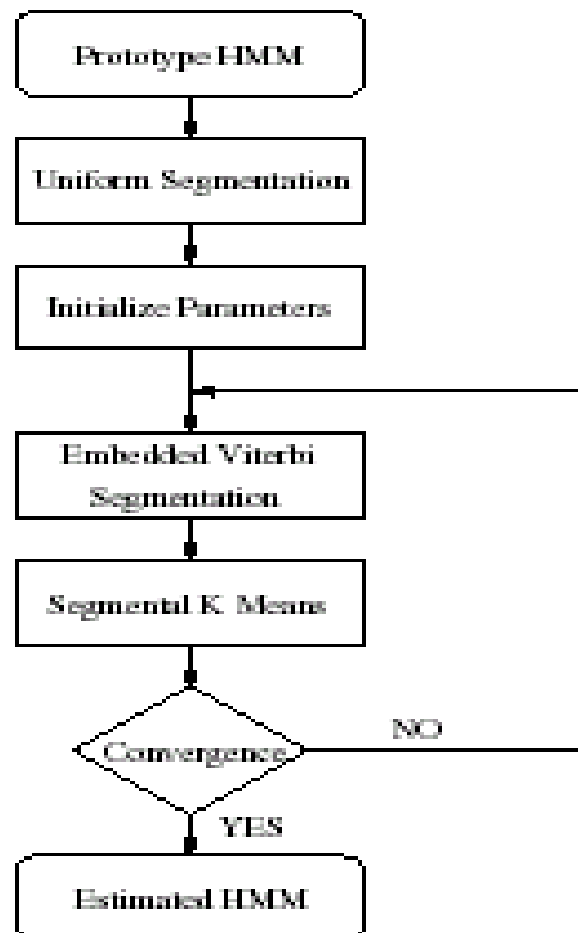
Face recognition using HMM

Training HMM

Hint: Encode the given observation sequences in such a way that if a observation sequence having many characteristic similar to the given one is encountered later, it should identify it.

(use k-means clustering algorithm)

Training of Images



HMM based Face recognition

- Get the observation sequence of test image. (obs_test)
- Given ($\lambda_1, \dots, \lambda_{40}$)
- Find likely hood of obs_test with each λ_i .
- The best likely hood identifies the person.
- Likely Hood = $P(\text{obs_test} | \lambda_i)$
- Hint:use viterbi algorithm again to get the sequence state for this obs_test sequence.

Dynamic Link Architecture

- The most successful feature-based structural matching approach has been the use of Elastic Bunch Graph Matching (EBGM) systems which is based on DLA.
- Local features represented by “jets” Which are derived from Gabor wavelet transformation.
- As use synaptic plasticity to from sets of neurons grouped into structured graphs in a neural network.

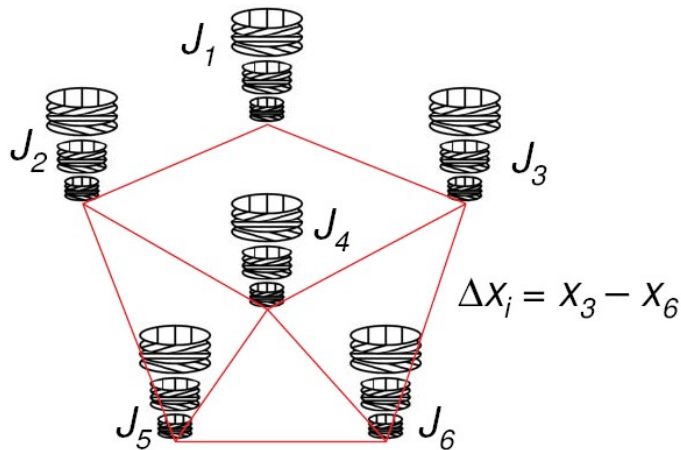
DLA Overview

- Human faces share a similar topological structure
- Labeled graph as basic object representation
 - Nodes positioned at fiducial points (eyes, nose...)
 - Jets at each node
 - Edges labeled with distance information
- Stored model graph matched to new images □ Image graph (can become model graph)
- Model graphs easily translated, scaled, orientated

Why bunch graphs?

- Different poses impose problems
- Labeled graphs useful for handling any kind of coherent object
- Face recognition is in-class discrimination of objects
necessary to have information specific to the
structure common to all objects in the class
 - too costly to generate own graph for each combination of
features Class specific information has the form of bunch
graphs (one for each pose).

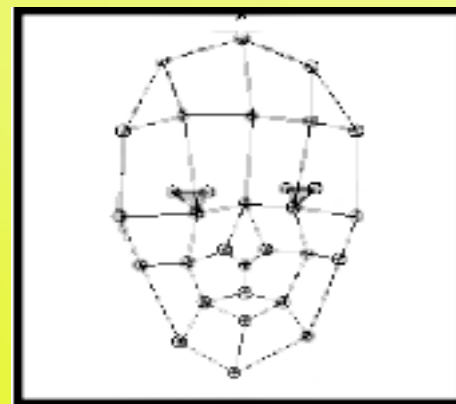
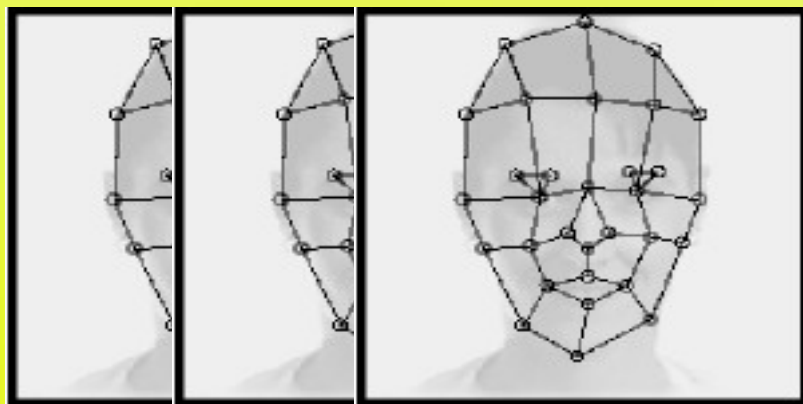
Image Graph



$$\Delta X_e = x_n - x_{n'}$$

- Image Graph G : N nodes, E edges
- Labeling of nodes:
Jets J_n at positions x_n , $n = 1, \dots, N$
- Labeling of edges:
Distances between nodes n and n'

Bunch Graph



Representative of a class:

Bunch graph

- General representation
- Combine Image graphs
 - Image graphs with same structure
- Stack like structure
- Same grid structure; nodes refer to identical fiducial points

Bunch Graph

- Constructing a Bunch graph B from M

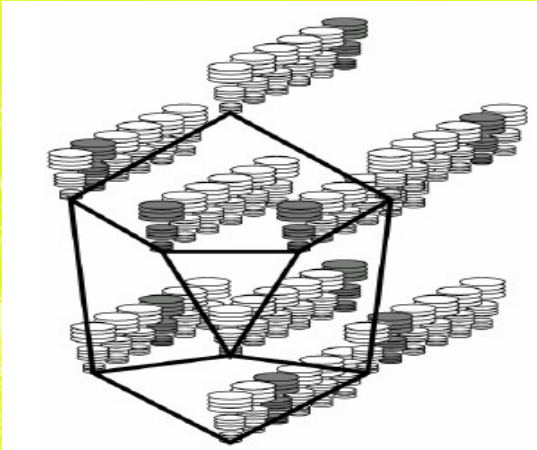


Image graphs G^{BM} :

- Summarize the jets from a node
→ Set of jets → “Bunch”
- Label nodes with Bunches
- Label edges with average distance

$$\Delta \mathbf{x}_e^{\mathcal{B}} = \frac{1}{M} \sum_m \Delta \mathbf{x}_e^{\mathcal{B}m}$$

DLA: Principle

- Based on dynamic link architecture
 - Extract facial feature by Gabor wavelet transform
 - Face is represented by a graph consists of nodes of jets
- Compare graphs by cost function
 - Edge similarity S_e and vertex similarity S_v
 - Cost function

$$C_{total}(G^I, G^M) = \lambda S_e(G^I, G^M) - S_v(G^I, G^M)$$

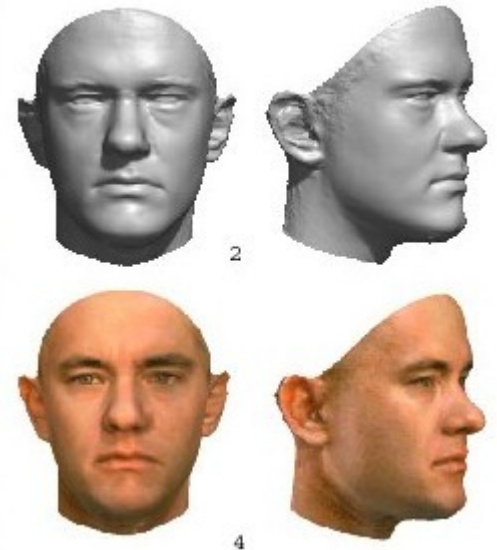
Hybrid Approach

- A sophisticated approach for face recognition.
- Similar to perception by Human Vision.
- It involves recognition using both Whole Face and the Local features like eyes, nose, mouth etc.

Component Based Method 3D Morphable Model



It represents each face by a set of model coefficients and generates new, natural looking faces from any novel set of coefficients.



3D Morphable Model

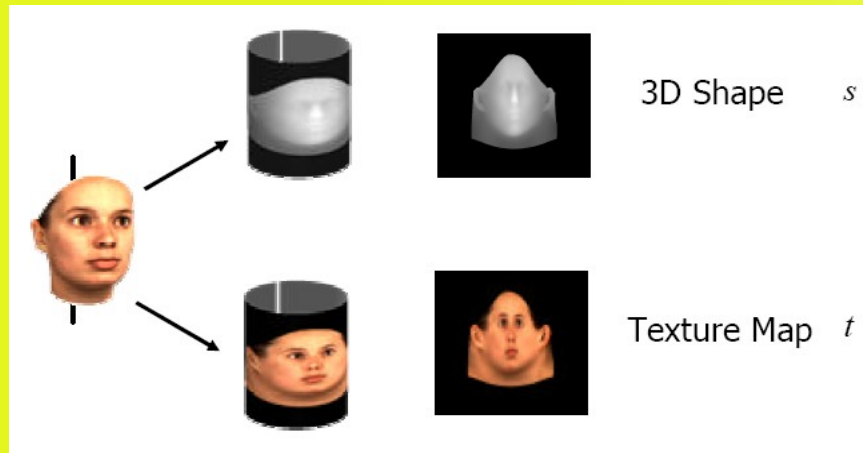
- A novel approach to pose and illumination invariant face recognition.
- No need of a large number of training images.
- Given a large database of generated 3D face models any arbitrary face can be generated by morphing between the ones in the database.
- The method used to create a 3D model from a set of 2D images is called ANALYSIS BY SYNTHESIS LOOP.

3D Morphable Model

- The actual 3D structure of known faces is captured in the shape vector

$$\mathbf{S} = (x_1, y_1, z_1, x_2, \dots, y_n, z_n)^T,$$

containing the (x, y, z) coordinates of the n vertices of a face, and the texture vector $\mathbf{T} = (R_1, G_1, B_1, R_2, \dots, G_n, B_n)^T$, containing the color values at the corresponding vertices.



3D Morphable Model

Again, assuming that we have m such vector pairs in full correspondence, we can form new shapes S_{model} and new textures T_{model} as:

$$S_{\text{model}} = \sum_{i=1}^m a_i S_i \quad T_{\text{model}} = \sum_{i=1}^m b_i T_i$$

$$s = \alpha_1 \cdot \text{img}_1 + \alpha_2 \cdot \text{img}_2 + \alpha_3 \cdot \text{img}_3 + \alpha_4 \cdot \text{img}_4 + \dots = \mathbf{S} \cdot \mathbf{a}$$

$$t = \beta_1 \cdot \text{img}_1 + \beta_2 \cdot \text{img}_2 + \beta_3 \cdot \text{img}_3 + \beta_4 \cdot \text{img}_4 + \dots = \mathbf{T} \cdot \mathbf{b}$$