Mosaicfaces: a discrete representation for face recognition

Jania Aghajanian and Simon J.D. Prince

{j.aghajanian,s.prince}@cs.ucl.ac.uk
Department of Computer Science, University College London
Gower St., London, WC1E 6BT, UK.

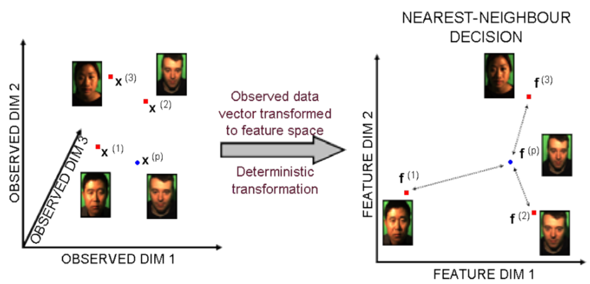
prince vision lab

EPSRC Engineering and Physical Sciences Research Council

UCL

1. Background and Motivation

Most face recognition methods e.g. eigenfaces[1] and Fisherfaces[2] make decisions based on a *distance measure.* Images are projected down to a lower-dimensional feature space. Distances between feature space representations are used as the basis for recognition.

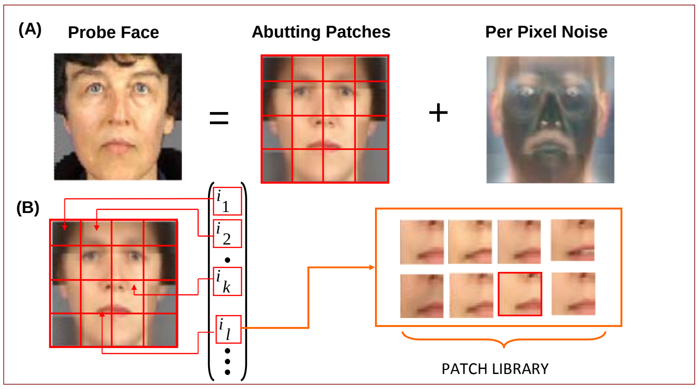


Limitations of current methods

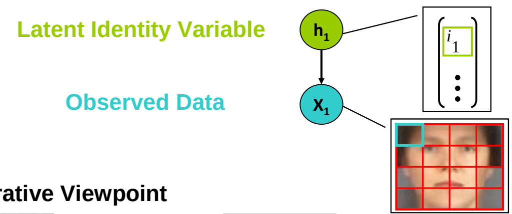
- Uni-modal: Model the face manifold using a single cluster
- Fail to model local texture variations

2. Mosaicfaces

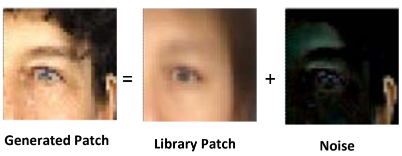
Representation: Our approach represents a face image as a composite picture made up of *non-overlapping* smaller patches. Each patch is taken from a library of discrete possibilities.



Learning: We use a probabilistic approach similar to [3] to learn a model for faces. At the core of our framework is that the data $\mathbf{x}_{ij}$ (i.e. a face) is generated from lower dimensional latent variables $\mathbf{h}_i$. These variables represent identity and are called *Latent Identity Variables* (LIV's).



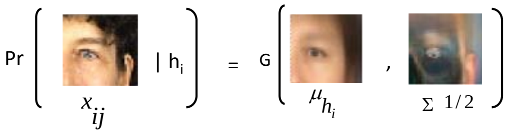
Generative Viewpoint



Probabilistic Viewpoint

$$Pr(\mathbf{x}_{ij}|h_i) = G(\mu_{h_i}, \Sigma)$$

$$Pr(h_i = k) = f_\mathbf{k}$$

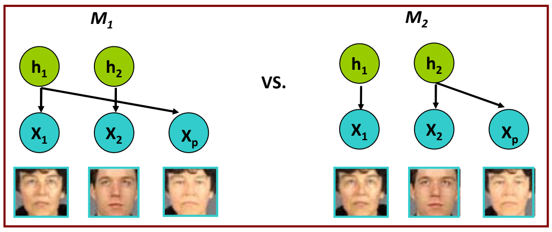


We learn the model parameters $\Theta = \{\mu_{1..K}, \Sigma_{1..K}, f_{1..K}\}$ using the Expectation-Maximization Algorithm [4].

1. M. Turk and A. Pentland. "Face recognition using eigenfaces," in Proc. *IEEE CVPR*, pp. 586-591, 1991.
2. V. Belhumeur, J. Hespanha, and D.Kriegman, "Eigenfaces vs. Fisherfaces: Recognition using class specific linear projection," *PAMI*, Vol. 19, pp. 711-720, 1997.
3. S.J.D. Prince and J.H. Elder, "Tied factor analysis for face recognition across large pose changes," in Proc. *BMVC*, Vol. 3, pp. 889-898, 2006.
4. A.P. Dempster, N.M Laird and D.B. Rubin, "Maximum Likelihood for incomplete data via the EM Algorithm," *Proc. Roy. Stat. Soc. B*, Vol. 39, pp.1-38, 1977.

Recognition: If two faces were generated from the same latent identity variable $\mathbf{h}_i$ hence they share identity and they belong to the same individual. We perform identification as model comparison.

Model: Hypothesize assignments between the data and the identity variables.

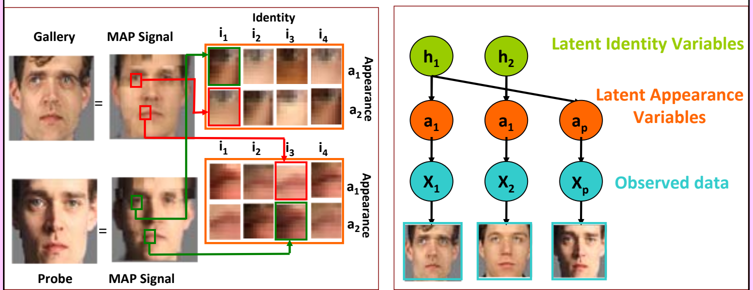


Match: Find the MAP model using Bayes' Rule.

$$\textbf{Bayes' Rule}: \quad Pr(M_1|x_1,x_2,x_p) = \frac{Pr(x_1,x_2,x_p|M_1)\ Pr(M_1)}{\sum_{n=0}^{N} Pr(x_1,x_2,x_p|M_n)\ Pr(M_n)}$$

3. Multiple Patch Appearances

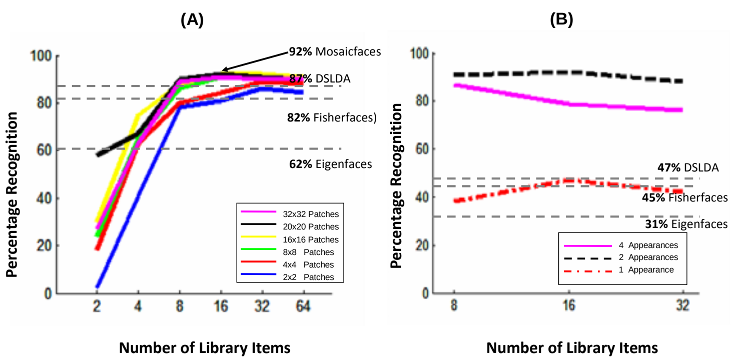
The standard mosaicface model cannot cope with large non-linear changes in the images, e.g. illumination. To deal with this problem we introduce a second set of latent variables into our model which lie between the latent identity variables $\mathbf{h}_i$ and the images $\mathbf{x}_i$.



Note: The probe and gallery images can take different appearance variables, however they still share an identity variable hence they are correctly identified.

4. Results and Comparison

Face identification with mosaicface model on XM2VTS database on the constant illumination (A) and varying illumination (B) sets. We divided the data into a training set of 195 individuals and a test set of 100 individuals. The test set contains 100 gallery images and 100 matching probe images.



Recognition performance increases as the number of library patches increase. The results also demonstrate an improvement as the image is divided into smaller patches. Peak performance is 92% with 16x16 patches and L=16 library items for each patch.

Multiple patch appearances improves the results of face identification regardless of non-linear variations in the data e.g. expression variation. Our performance compares favorably to that of contemporary algorithms

5. Conclusions

- Novel representation of faces for face recognition
- No distance metric
- Models data manifold with a multimodal density
- Significant improvement over distance based methods in presence of large intra-class variations