# Image Statistics Based on Diffeomorphic Matching



Guillaume CHARPIAT<sup>1</sup>, Olivier FAUGERAS<sup>2</sup>, Renaud KERIVEN<sup>3</sup>

<sup>1</sup> Projet Odyssée, École Normale Supérieure, France

<sup>2</sup> Projet Odyssée, INRIA Sophia Antipolis, France

<sup>3</sup> Projet Odyssée, École Nationale des Ponts et Chaussées, France



#### Introduction

- Goal: non-supervised object recognition, image classification
- $\hookrightarrow$  automatic description of shape and colour variations ?
- Method: compute a *mean* object and *characteristic modes of variation*
- **Basic Tool** : non-supervised diffeomorphic image matching

#### **Modes of Shape Variation**

- **Data:** n images  $I_i$ , n warping fields  $h_i$
- Method: warping field statistics
- Correlation between 2 fields:  $\langle h_i | h_j \rangle = \int h_i(y) \cdot h_j(y) \, dy$
- Modes: diagonalization of correlation matrix, extraction of eigenmodes  $P_k$  and their eigenvalues  $\sigma_k$

- $\hookrightarrow$  natural definition of mean and modes
- Advantages: non-supervised, non-specific to a particular dataset
- Example: Yale face image dataset
- Classification Application: face expression recognition task

### **Diffeomorphic Image Matching** $h^{-1}$ • Initial Image: A • Target Image: B • Method: search for a diffeomorphism h such that $A \circ h \simeq B$ Image $A \circ h$ Image A

• Image Similarity Criterion: Local Cross-Correlation (LCC)

 $LCC(A,B) = \int_{y\in\Omega} \frac{v_{AB}(y)^2}{v_A(y) v_B(y)} dy$ 

• Example: application of the modes to the mean image M with different amplitudes



#### Modes of Shape and Intensity Variation

• Intensity Variations:  $v_i = I_i \circ h_i - M$ 

- with  $v_A(y)$  local variance of image A in a gaussian neighborhood of point y, and  $v_{AB}(y)$  the local covariance
- Smoothing Term: for example  $R(h) = ||h \mathrm{Id}||_{H^1}$
- Image Matching: multiscale gradient descent with respect to warping field h of

 $E(A, B, h) = R(h) - LCC(A \circ h, B)$ 

Some initial images  $I_i$  from the dataset

#### **Computation of the Mean Image**



















#### Together warped images $I_i \circ h_i$



Mean image M(sum of the warped images) • Intensity Variation Correlation:  $\langle v_i | v_j \rangle = \int_{\Omega} v_i(y) v_j(y) dy$ • Combined Shape-Intensity Correlation:  $\langle h_i, v_i | h_j, v_j \rangle = \langle h_i | h_j \rangle + \langle v_i | v_j \rangle$ 

• New Modes: with 2 parts (deformation field and intensity modification field)



## **Classification Task: Face Expression** Recognition

• Goal: associate, to any new face, its expression (among 5 given expressions) • **Data:** a training set, a new face with and without expression

• Method: compare the warping field between the 2 new images to known labeled fields (after alignment to the mean face). Result: 53/65. Incorrect labels are marked.



- **Data:** set of n images  $I_i$
- Goal: computation of a mean image M
- **Problem:** gradient descent involving M intensity leads to local minima  $\hookrightarrow$  creation of new contours instead of moving existing ones
- Solution: use diffeomorphisms
- $\hookrightarrow$  associate to each image  $I_i$  a diffeomorphism  $h_i$

 $\hookrightarrow$  minimize with respect to the *n* fields  $h_i$  the similarity between all warped images

$$\sum_{i} R(h_i) - \frac{1}{n-1} \sum_{i \neq j} LCC(I_i \circ h_i, I_j \circ h_j)$$
  
• Mean Image:  $M = \frac{1}{n} \sum_{i} I_i \circ h_i$ 



• Algorithm Comparison: SVM on images leads to 17 errors instead of 12. • Without Normal Face: use warping field from the mean face to the new face. Result: 41/65 (SVM on images: 38).