Set-to-Set Face Recognition Under Variations in Pose and Illumination

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Jen-Mei Chang, Michael Kirby, Chris Peterson

Department of Mathematics

Colorado State University

INTRODUCTION

Face recognition under variations in illumination and pose has been recognized as a difficult problem with pose appearing somewhat more challenging to handle than variations in illumination (Zhao et al., 2003).

What's Known About Illumination:

- Subject illumination cone is linear (Belhumeur & Kriegman, 1998) and low-dimensional (Basri & Jacobs, 2003).
- Illumination face spaces are idiosyncratic (Chang et al., 2006).

What's Known About Pose:

- Subject pose manifold is nonlinear.
- Linear methods perform poorly on this problem (e.g. SVD-based).

Past Approaches:

- Illumination cone (Georghiades et al., 2001).
- Light-fields (Gross et al., 2004).
- 3D Morphable Model (Blanz & Vetter, 2003)

Past Classification Method:

- Comparing distances of a single incidence of the probe class with a single or multiple incidence(s) of the gallery classes.
- Euclidean or statistical measure of similarity.

PROPOSED METHOD

- We propose to use set-to-set comparison paradigm for face recognition where we assume multiple images of each subject are available.
- This paradigm naturally induces classification on the *Grassmannians* (definition is given below), where well-established metrics (Edelman et al., 1999) are available for classification (examples given below).
- Any attempt to construct a unitarily invariant metric on the Grassmann manifold will yield something that can be expressed in terms of *principal angles*.

Definition

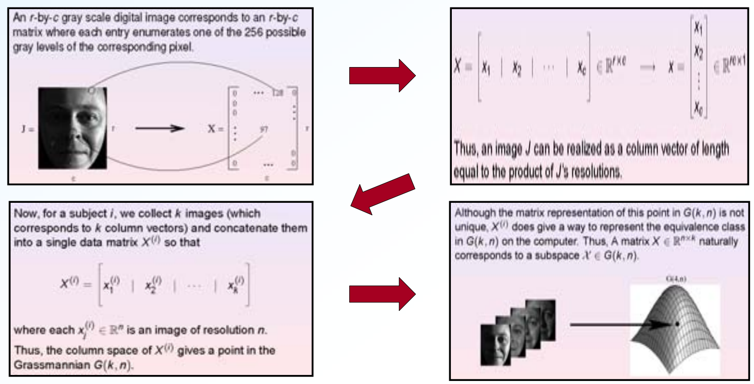
The Grassmannian $G(k,n)$ or the Grassmann manifold is the set of k-dimensional subspaces in an n-dimensional vector space K^n for some field K. i.e.,

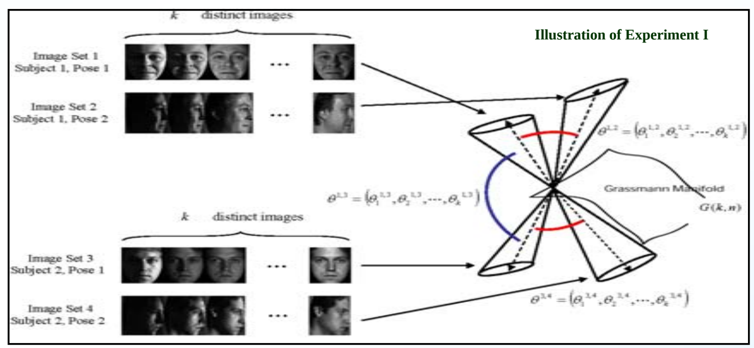
$$G(k,n) = \{W \subset K^n \mid \dim(W) = k\}.$$

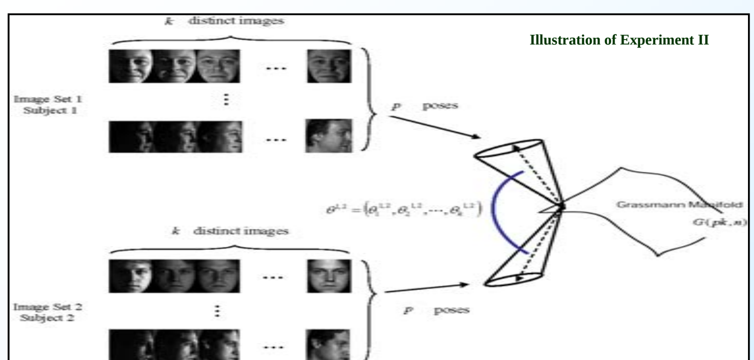
Example Metrics

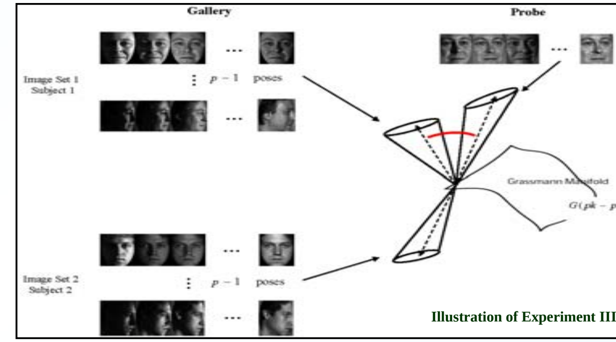
Arc length (Geodesic)	$d_g(X,Y) = \|\theta\|_2$
Fubini-Study	$d_{FS}(X,Y) = \cos^{-1}\left(\prod_{i=1}^{k} \cos\theta_i\right)$
Chordal (Projection F)	$d_c(X,Y) = \|\sin\theta\|_2$

Classification on the Grassmannians









RESULTS

- *Extended Yale Face Database B (YDB)* (Georghiades et al., 2001).
  28 subjects, 9 poses, 65 illumination conditions
- The *``illum'' subset of CMU-PIE database* (Sim et al., 2003).
  67 subjects, 13 poses, 21 illumination conditions

Fig. 2. Example images in the Extended YDB.

Error Rate (%)	Experiment		
Database	I	II	III
Extended YDB	0	0	6.7
CMU-PIE	0	0	26.9

Table 1. Average recognition error rate for Experiments I, II, and III using the first principal angle. Poses c07, c09, c25, and c31 are excluded in Experiment III of the CMU-PIE.

DISCUSSIONS

- Set-to-set paradigm is done by realizing sets of images as points on a Grassmann manifold and employ a geometric perspective for computing metrics that compare subspaces and extract neighborhood information.
- Sufficient sampling of the variation is critical and in the illumination and pose problem, it is more important for pose than illumination.
- No geometric normalization and preprocessing is required.
- Most of the computation is done off-line, therefore making the method efficient. See Table 2 for a short comparison of the speed.

	3DMM	Illumination Cone	Set-to-Set
Data set used	"lights" of PIE	YDB	"illum" of PIE
Image pixel size	200 × 200	42 × 36	367 × 401
Identification time for one probe	2.5 min. Pentium IV 2.0GHz	2.5 sec./gal. ind. Pentium II 300MHz	0.65 sec./gal. ind. AMD Opteron 8220SE 2.8 GHz

Table 2. Computational speed of the two state-of-the-art face recognition algorithms and the proposed set-to-set algorithm.