Recognition of Digital Images of the Human Face at Ultra Low Resolution via Illumination Spaces

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INTRODUCTION

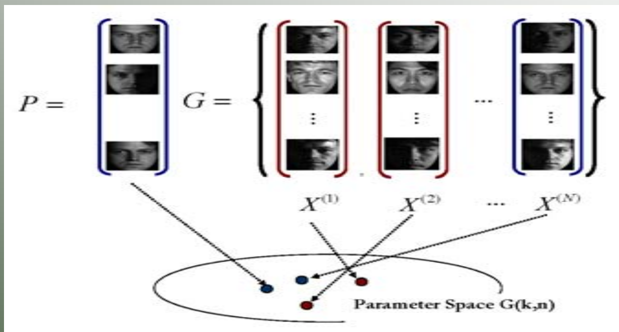
Recent work has established that digital images of a human face, collected under various illumination conditions, contain discriminatory information that can be used in classification. In this work, we demonstrate that sufficient discriminatory information persists at ultra low resolution to enable a computer to recognize specific human faces in settings beyond human capabilities.

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).

GRASSMANN METHOD

- 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 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 gives 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.,

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

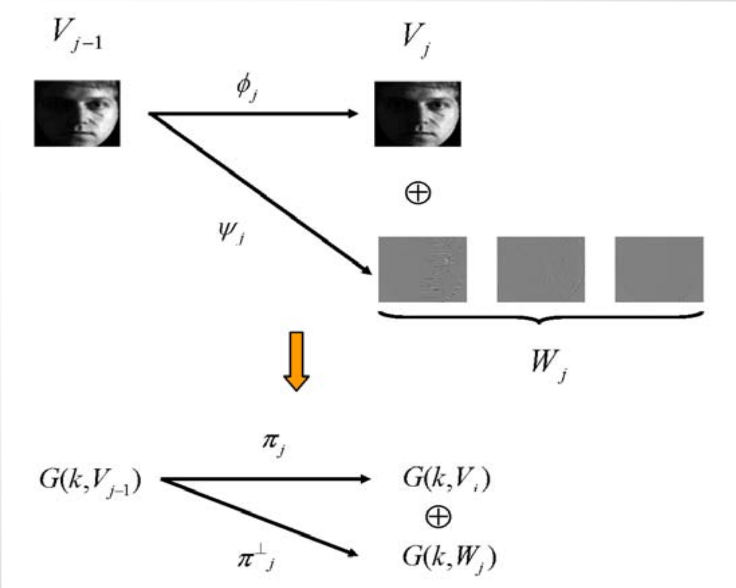
Example Grassmannian Metrics

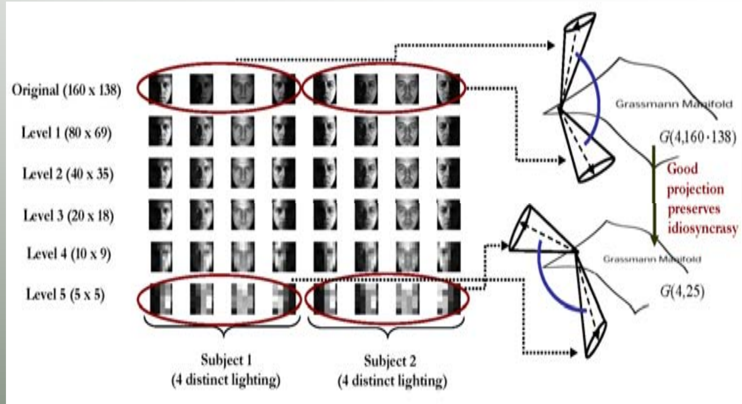
Arc length (Geodesic) $d_g(X,Y) = \|\theta\|_2$

Fubini-Study $d_{FS}(X,Y) = \cos^{-1}\left(\prod_{i=1}^{k} \cos\theta_i\right)$

Chordal (Projection F) $d_c(X,Y) = \|\sin\theta\|_2$

RESOLUTION REDUCTION

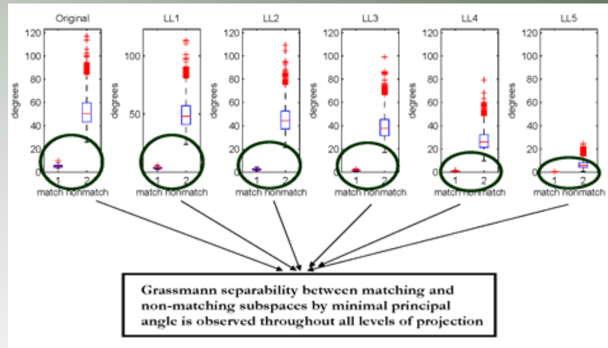




RESULTS: A 25-pixel Illumination Camera

➢ The *``illum'' and ``lights'' subsets of CMU-PIE database* (Sim et al., 2003).

67 subjects, 13 poses, 21 illumination conditions



COMPUTATIONAL COMPLEXITY

(Computation of large principal angles, Björck & Golub, 1973) Define $F = \mathcal{R}(A)$, $G = \mathcal{R}(B)$, where A is in $\mathbb{R}^{n\times p}$ and B is in $\mathbb{R}^{n\times q}$. Principal angles are defined to be between 0 and $\pi/2$ and listed in ascending order.

Input: matrices A (n-by-p) and B (n-by-q).

Output: principal angles θ and cosine of the principal angles between subspaces $\mathcal{R}(A)$ and $\mathcal{R}(B)$, C.

1. Find orthonormal bases Q_a and Q_b for A and B such that

$$Q_a^T Q_a = Q_b^T Q_b = I \quad \text{and} \quad \mathcal{R}(Q_a) = \mathcal{R}(A), \mathcal{R}(Q_b) = \mathcal{R}(B).$$

2. Compute the SVD of $Q_a^T Q_b$: $Q_a^T Q_b = UCV^T$, so that $\operatorname{diag}(C) = \cos\theta$.

E.g., it takes approximately 0.000218 seconds to compute a distance between 2 points in G(10,25) on a 2.8 GHz AMD Opteron processor.

DISCUSSIONS

- Classification with Grassmann method 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.
- Grassmann separability persists at ultra low resolution since the idiosyncratic nature of the illumination spaces is preserved throughout all levels of good projections.
- An immediate application: large *private* databases of facial imagery can be stored at a resolution that is sufficiently low to prevent recognition by a human operator yet sufficiently high to enable machine recognition.

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