Bypassing Synthesis : PLS for Face Recognition with Pose, Low-resolution and Sketch

Abhishek Sharma and David W. Jacobs

One ring (PLS) to rule (Recognize) them all (modalities)

Problem Statement

Comparing apples to oranges : Given a subject's face image in some modality (pose, sketch, low - resolution) that is different than the gallery image modality, how to find a match?

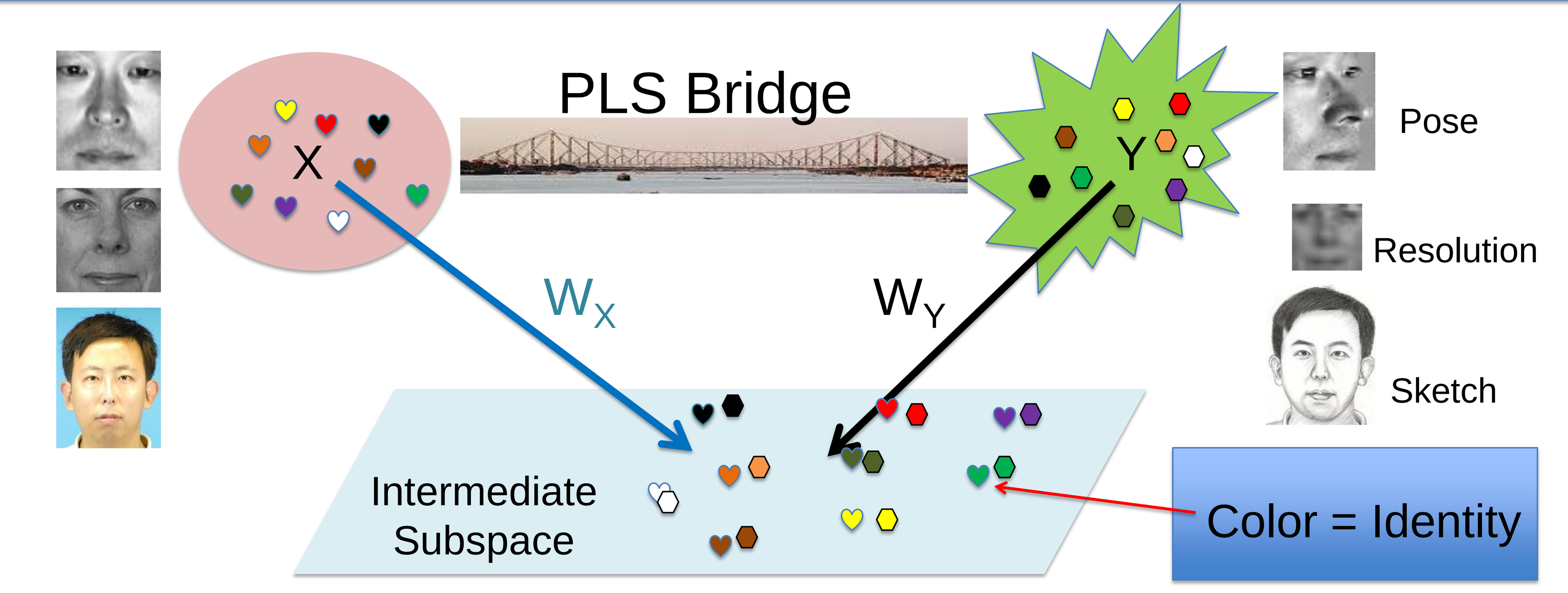
Earlier Approaches and drawbacks

- Virtual view synthesis - Great but its slow.
- Stereo matching – Robust and accurate but slow and only for pose.
- CCA and Bilinear Model – Fast but suboptimum.

Partial Least Square (PLS) based proposed approach

- Use PLS to learn two projection directions W_X and W_Y from a training set {X, Y} (subject's images in two modalities).
- **Projection in intermediate subspace maximizes covariance between same subject's images in different modality.**
- 1-NN matching followed by projection.
- Accurate and very fast **online.**
- Exactly same framework works well for pose, sketch and low-resol.
- **State-of-the-art for pose-invariant face recognition on CMU PIE.**

PLS based proposed method flow diagram

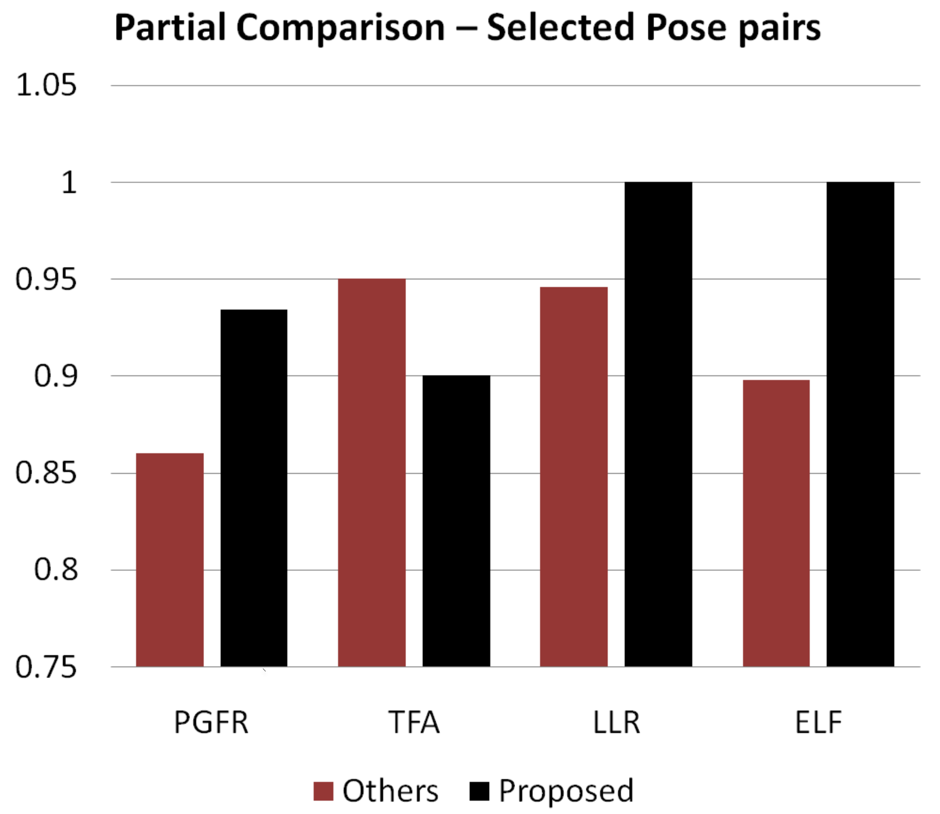


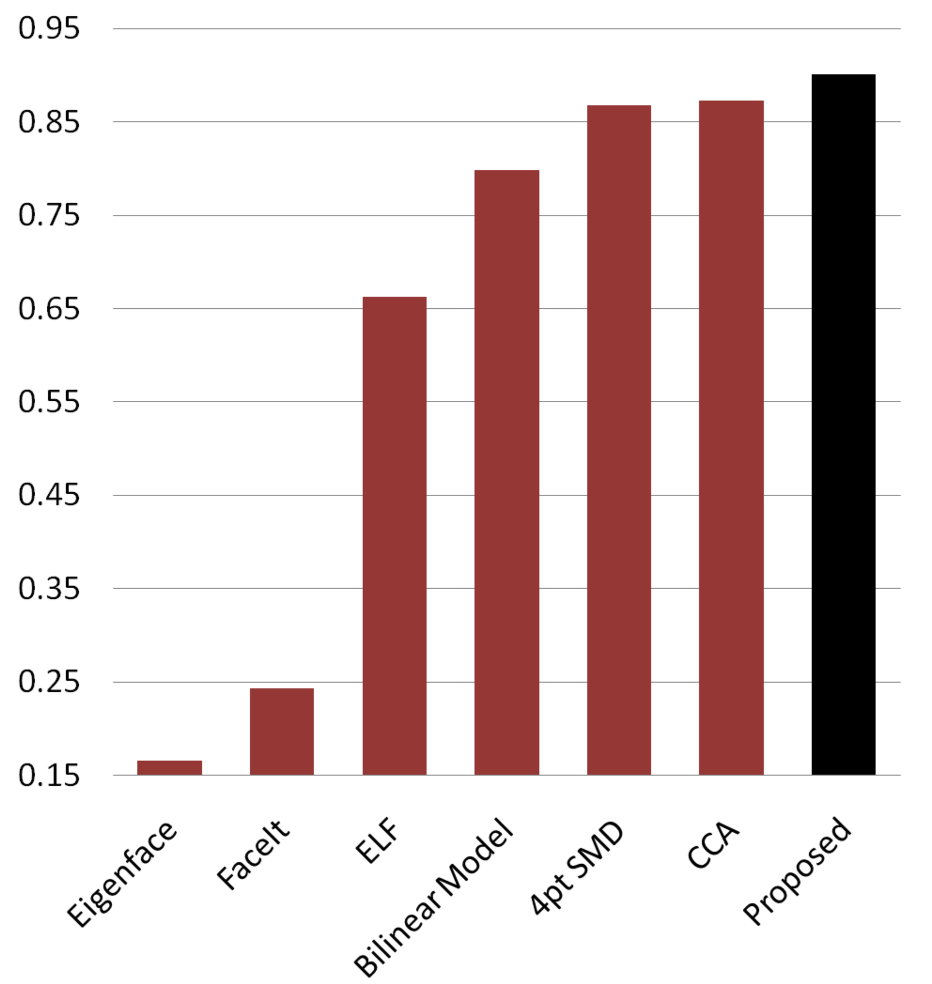
Experiments

All the modalities tested using one simple generic algorithm.

Pose Invariant Face Recognition

- CMU PIE face date set for experiments
- 34 training and 34 testing, intensity features

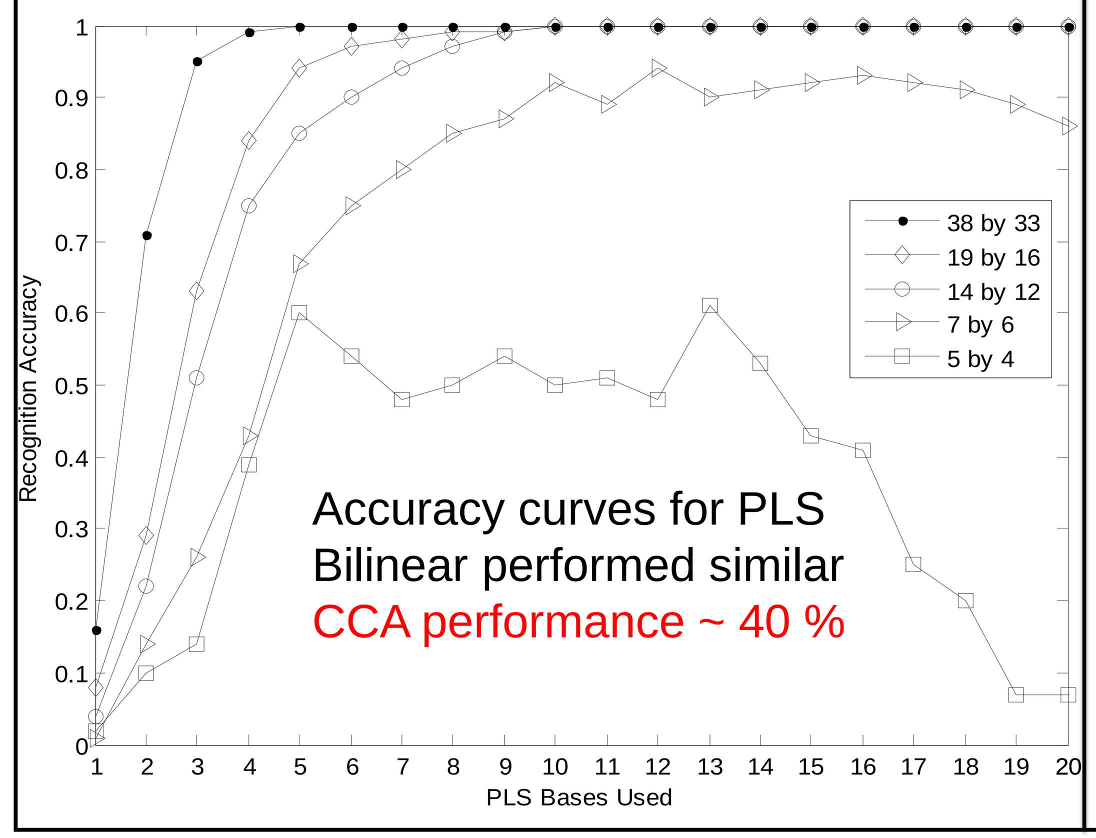




Low-Resolution (toy experiment)

-- Low - res images synthesized from FERET

-- High - Res images of size 76 by 66



Sketch – Face recognition

-- CUHK Face-Sketch dataset.

-- 88 training, 100 testing, intensity.

Method	Gal. Size	Type	Accuracy
Wang	100	Holistic	81
Liu	300	Patch	87.67
Klare	300	Pixel	99.47
PLS	100	Holistic	93.6
CCA	100	Holistic	94.6
Bilinear	100	Holistic	94.2

Theory and Discussion

X and Y are two view of same info, W_X and W_Y two projection directions

Partial Least Square (PLS)

$$X = TW_X^T + E \qquad Y = UW_Y^T + F \qquad U = TD + G$$

$$s.t.\ \max[\mathbf{cov}(XW_{X_i}, YW_{Y_i})] \quad \forall i \in \{1,2,\ldots k(\#bases)\}$$

- ✓ **PLS -** Maximizes covariance in the intermediate space.
- ✓ **PLS -** Optimum balance of discrimination and correlation.
- ✓ **PLS -** Performance not sensitive to # bases used.
- ✓ **PLS, CCA & BLM –** Can be kernelized.

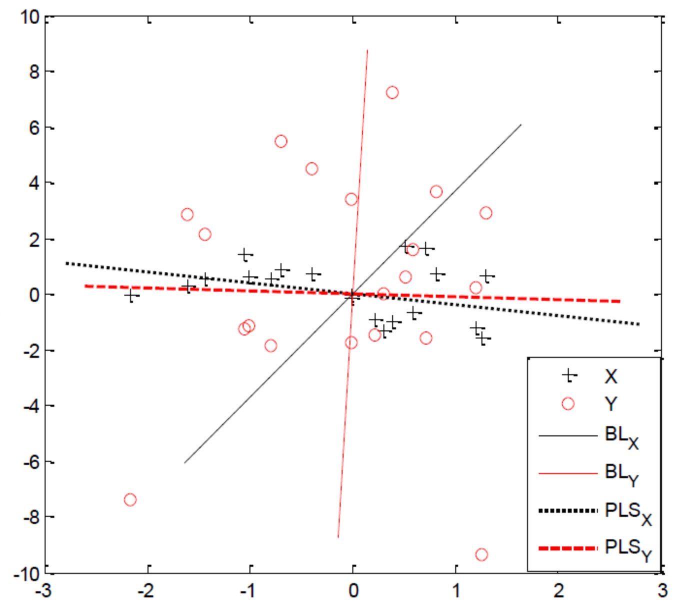


Fig 2 PLS vs. Bilinear Model (BL), horizontal coordinates of X and Y are same and vertical coordinates are uncorrelated

- ✖ **CCA -** Captures correlation only ($\max[\mathbf{corr}(XW_{X_i}, YW_{Y_i})]$).
- ✖ **BLM -** No *explicit* effort to capture correlation.
- ✖ **PLS, CCA & BLM -** Discard label information.
- ✖ **PLS** - Poor performance for more than two modalities.
- ✖ **PLS** - Greedy, Iterative and computationally intensive *offline.*

All three were able to find **linear** mappings from one pose to other which are basically permutations with averaging and supposed to be highly non-linear and difficult to learn. It highlights the promising future aspects of the proposed approach.

SIMPLS for W_X(W) and W_Y(Q)

Define: $A_0=X'Y$; $M_0=X'X$; $C_0=I$; c = #bas

For each h = 1,…,c

Do

1. Compute q_h the dominant eigenvector of $A_h'A_h$;

2. $w_h=A_hq_h$; $c_h=w_h'M_hw_h$; $w_h=w_h/sqrt(c_h)$; store w_h into W as column

3. $p_h=M_hw_h$; store p_h into P as a column.

4. $q_h=A_h'w_h$; store q_h into Q as a column.

5. $v_h=C_hp_h$; $v_h=v_h/||v_h||$;

6. $C_{h+1}=C_h - v_hv_h'$; $M_{h+1}=M_h - p_hp_h'$

7. $A_{h+1}=C_hA_h$

End For each