# Face Recognition Under Varying Viewing Conditions with Subspace Distance

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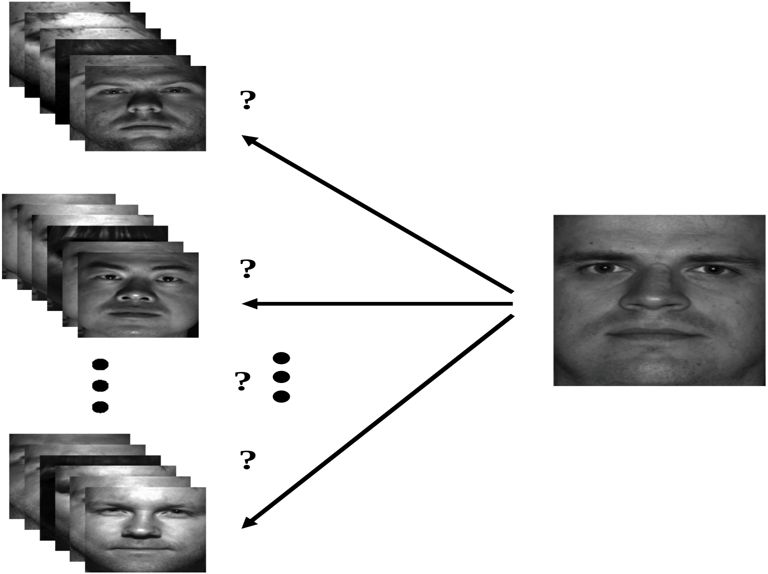
# Outline



# Database

Yale Face Database B (YDB) (Georghiades et al., 2001).

### Illumination

### Pose

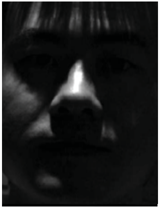
# Motivation for Multi-Set Distances

Images of a single person seen under variations of illumination appear to be more difficult to recognize than images of different people (Zhao et al., 2003).

Subject 1

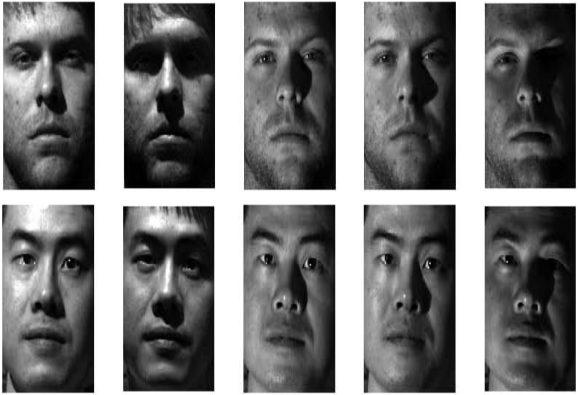
Subject 2

Can you tell who this is?



# Motivation for Multi-Set Distances

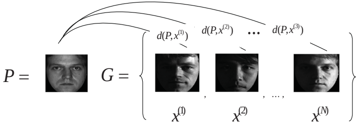
Can you tell them apart now?



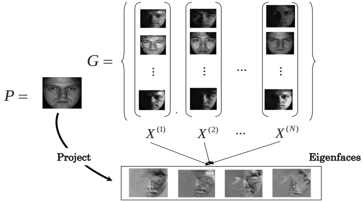
# Architectures

## Traditionally

1. single-to-single

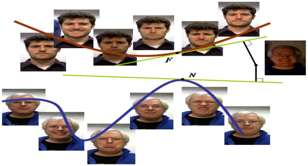



2. single-to-many

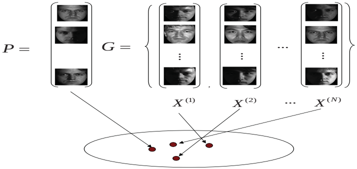



## Currently

- subspace-to-subspace

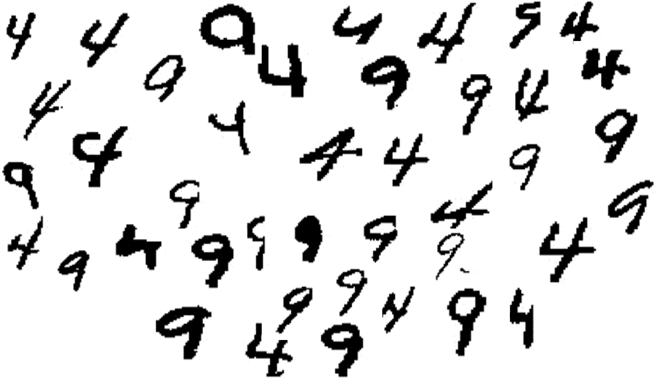



- many-to-many



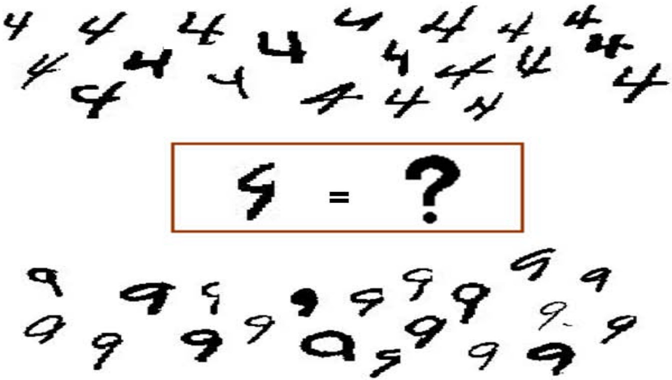
# Handwritten Digit Classification

The first use of tangent distance in a pattern recognition problem was for the handwritten digit classification (Simard et al., 2001).



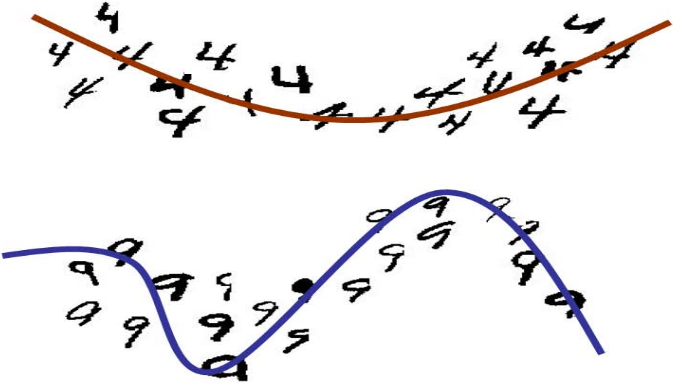
# Handwritten Digit Classification

How do we tell whether a new digit is a 4 or a 9?



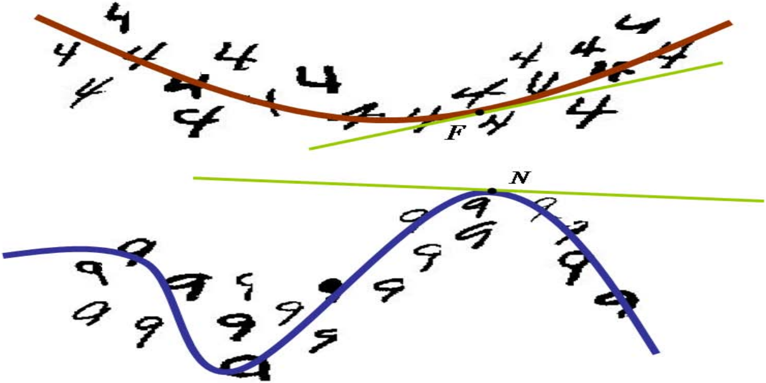
# Digit Manifolds

Imagine a high-D surface (red curve) where all 4's live on and a high-D surface (blue curve) where all 9's live on.



# Tangent Spaces - Training

Create a Tangent Space of the 4's at $F$ and create a Tangent Space of the 9's at $N$.




Dimensions of the tangent spaces depend on the degree of variations.

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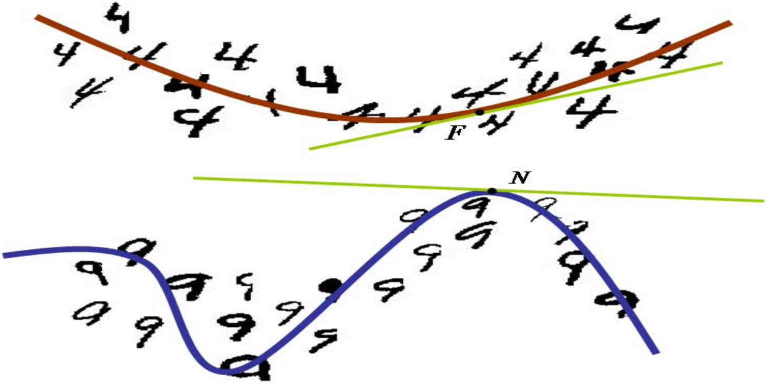


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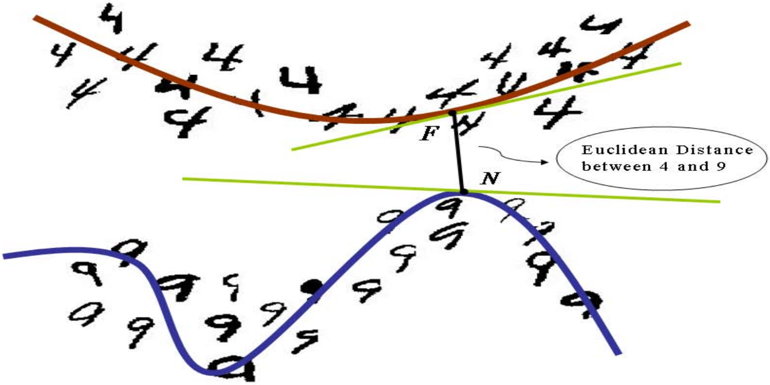
# Euclidean Distance




- Euclidean distance between each pair of 4 and 9 varies drastically.
- Calculation is time-consuming.

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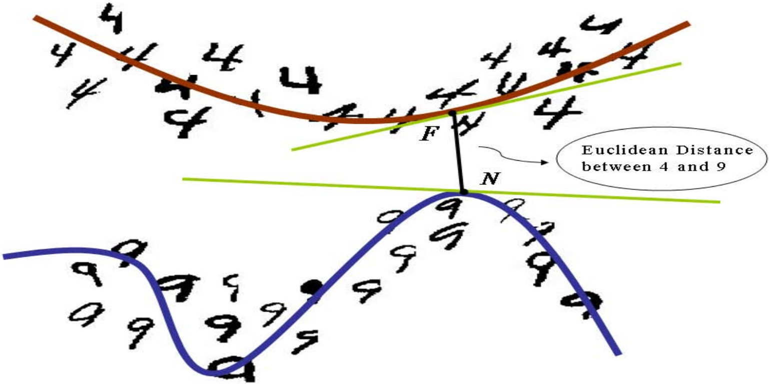


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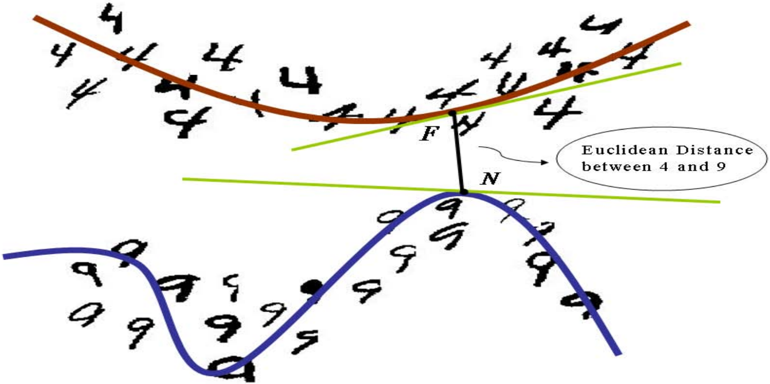


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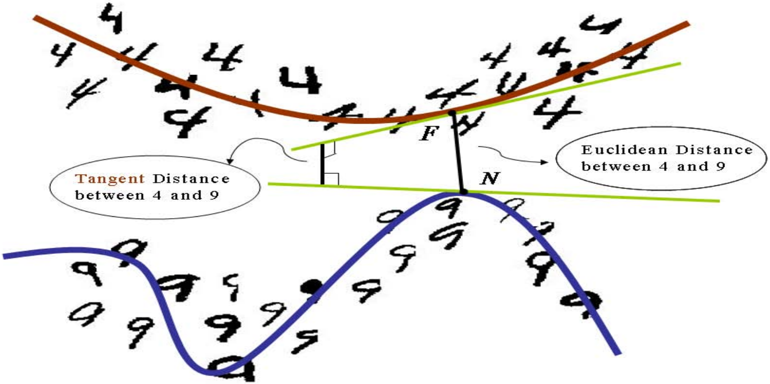


- Tangent distance captures the geometry.
- Calculation is efficient.

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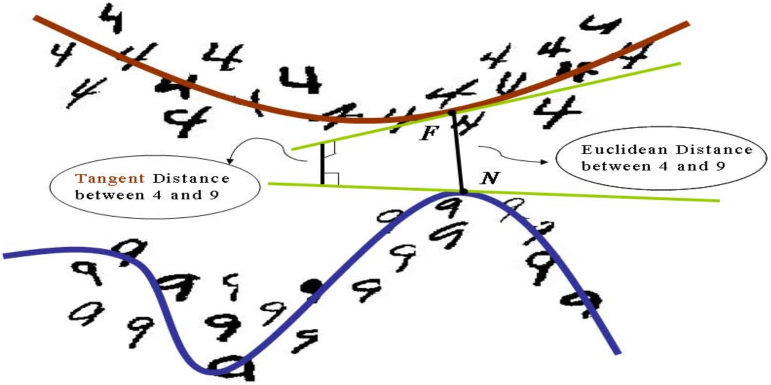


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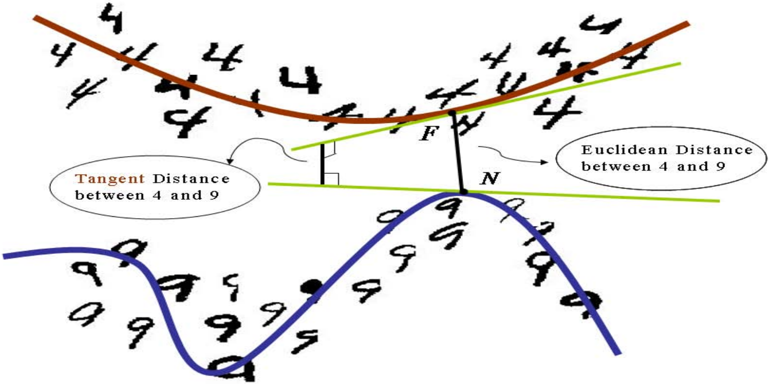
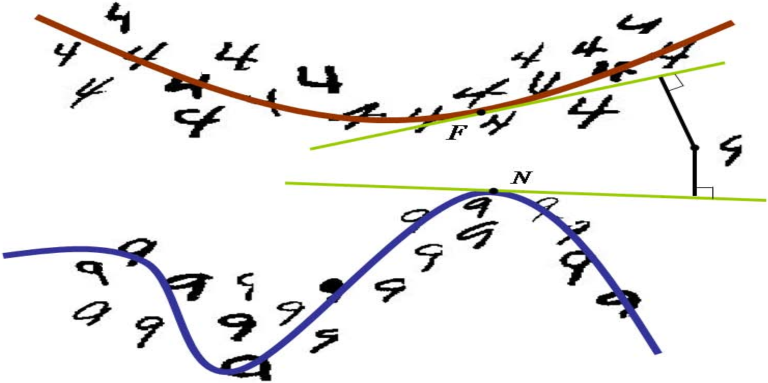


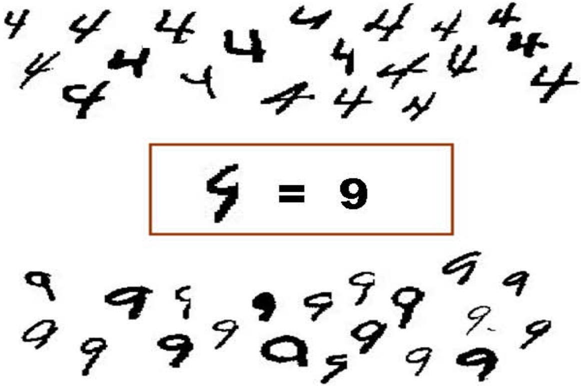

- Tangent distance captures the geometry.
- Calculation is efficient.

# Classification

So, is it a 4 or a 9?

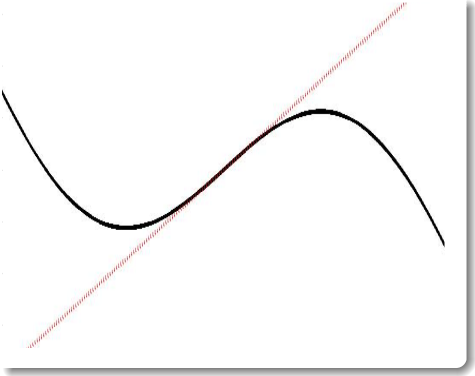


# Classification Result



# Subspace Distance

Instead of approximate the manifold with a *linear* subspace, use higher dimensional ones.



We, hence, call the distance between these higher dimensional subspaces the *subspace distances*.

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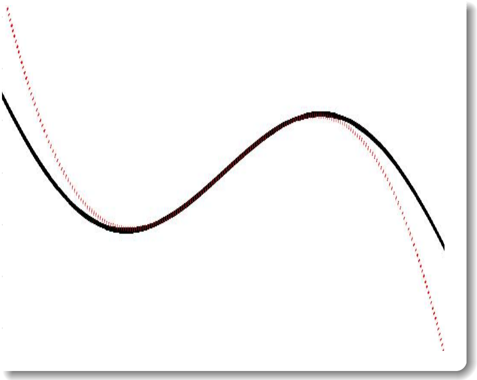

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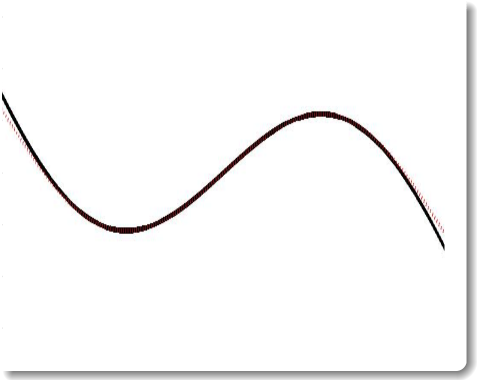

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# Experimental Design

- **YDB Pose Data,** $X_P$**.** 90 images of 10 individuals each seen under a fixed point light source with 9 distinct pose conditions.
- **YDB Illumination Data,** $X_I$**.** 640 images of 10 individuals each seen under frontal pose with 64 distinct lighting conditions.
- Increase pose data by including mirror images to form $\hat{X}_P$.
- Adopt a leave-one-out cross-validation routine for error estimates.
- Error reports for the following two parameters:
    1. Subspace dimension.
    2. Cardinality of training images.

# $X_P$: Subspace Dimension

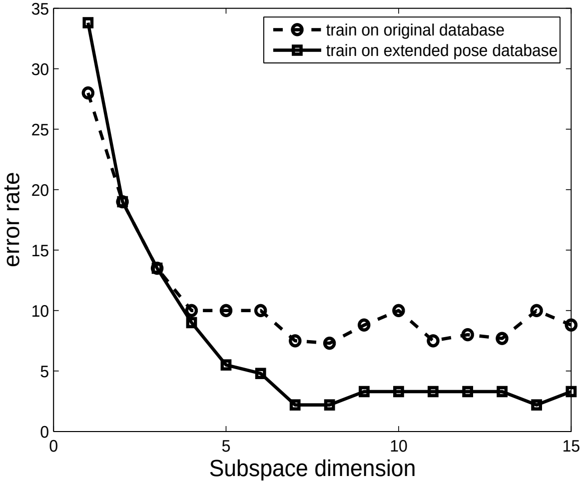


Figure: Error rate versus subspace dimension when the classifier is trained on $X_P$ and $\hat{X}_P$, respectively.

# $X_P$: 7D Subspace Distance

(a) Images missed when trained on $X_P$

(b) Images missed when trained on $\hat{X}_P$

# $X_P$: Cardinality of Training Set

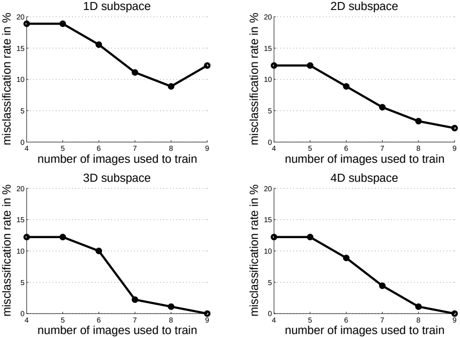


Figure: Error rate versus cardinality of training set on $X_P$.

| | $X_P$ | $\hat{X}_P$ |
|---|---|---|
| 2 | 81.1 | 81.1 |
| 6 | 90 | 95.6 |
| 7 | 92.2 | 97.8 |
| 8 | 91.1 | 97.8 |

Table: A sample of recognition rate versus subspace dim. on $X_P$ and $\hat{X}_P$.

# $X_I$: Subspace Dimension

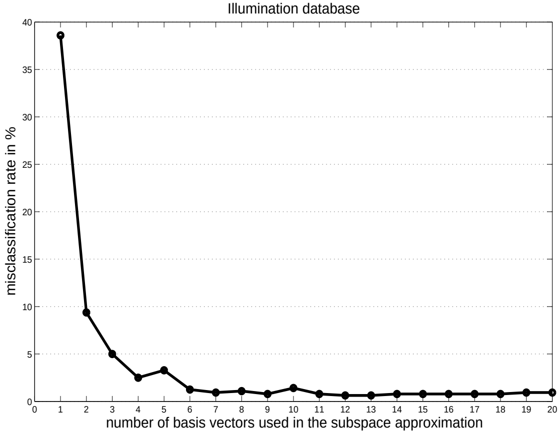


Figure: Error rate versus subspace dimension when the classifier is trained on $X_I$.

# $X_I$: 12D Subspace Distance

Figure: Images missed when trained on $X_I$.

# $X_I$: Cardinality of Training Set

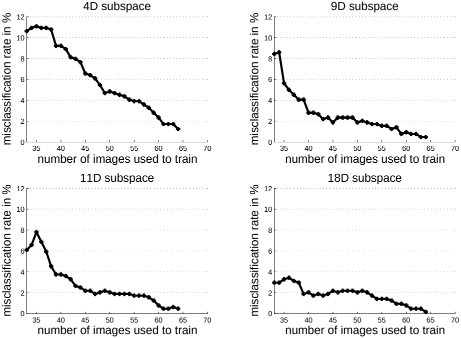


Figure: Error rate versus cardinality of training set on $X_I$.

| | $X_I$ |
|---|---|
| 2 | 90.63 |
| 6 | 98.75 |
| 9 | 99.22 |
| 12 | 99.38 |

Table: A sample of recognition rate versus subspace dim. on $X_I$.

# Summary

- Tangent space/distance $\Rightarrow$ subspace distance.
- This model is a feature-invariance one that can be extended to any type of variation.
- The model will benefit from having ample training samples.

# Open Areas and Future Directions

- Curvature information.
- Combination of illumination and pose variations.
- Other types of set-to-set classification paradigm.

# References

**(Georghiades et al., 2001)** A. Georghiades, P. Belhumeur, & D. Kriegman, “From few to many: Illumination cone models for face recognition under variable lighting and pose”, *PAMI, 23(6):643–660, 2001*.

**(Simard et al., 2001)** P. Simard, Y. Cun, J. Denker, & B. Victorri, “Transformation invariance in pattern recognition – tangent distance and tangent propagation”, *IJIST, 11:181–194, 2001*.

**(Zhao et al., 2003)** W. Zhao, R. Chellappa, P. J. Phillips, A. Rosenfeld, “Face recognition: A literature survey”. *ACM Comp. Surv., 35(4):399–458, 2003*.