Modeling Appearance Patterns in Image Sets

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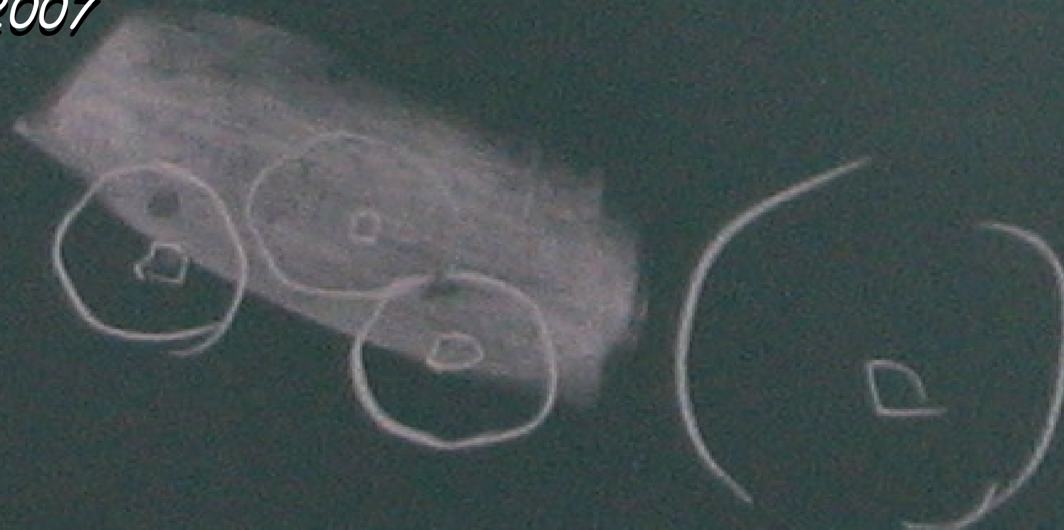
ECSE 626

February 12, 2007



2-Lecture Overview

1) Image Features (February 9, 2007)
   - Corners, edges, SIFT.
   - **Single images**, matching.

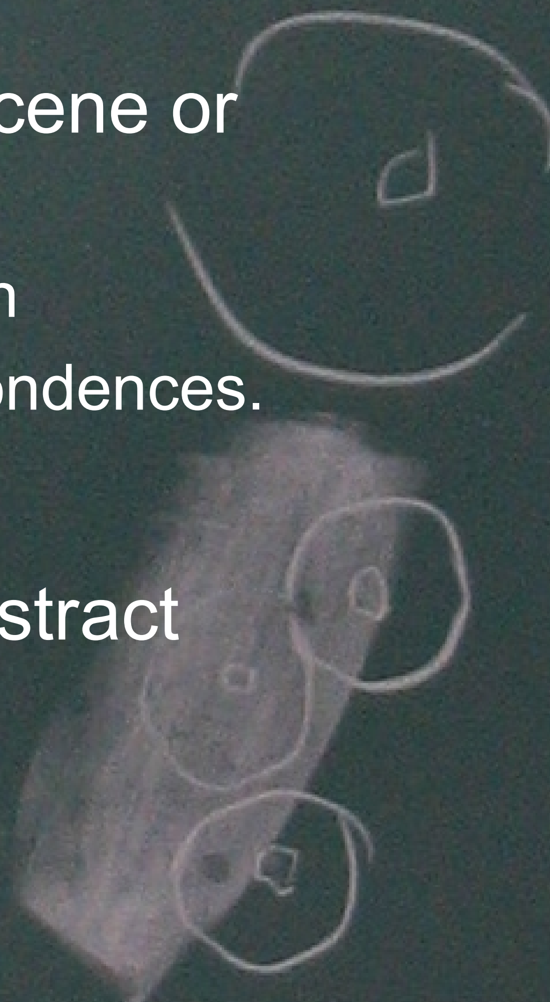
2) Probabilistic Modeling (February 12, 2007)
   - Learning how features behave over **many images**.

Overview

- Problem
  - Feature matching is ineffective for abstract patterns or object classes.
- Solutions
  - Learning appearance patterns from many examples.
- Object Class Invariant
  - Modeling appearance patterns over viewpoint change.

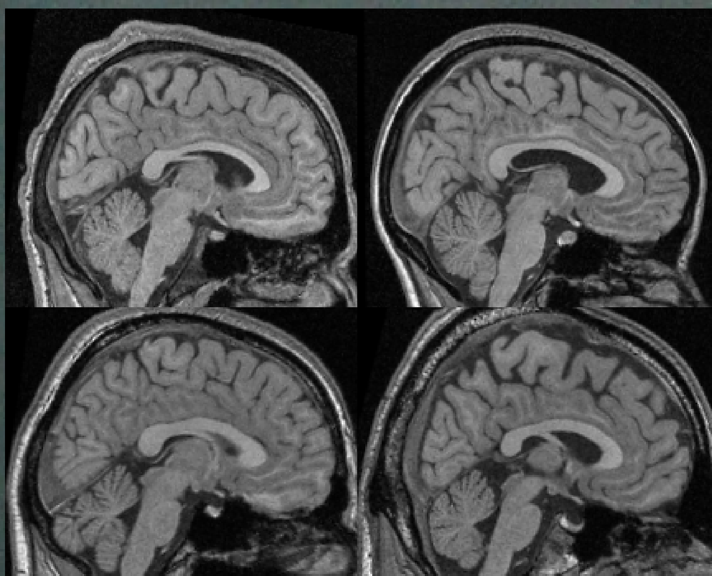
Local Feature Matching

- Strength:
  - Matching images of the same scene or object.
    - Template-based object recognition
    - 3D scene geometry from correspondences.
- Weakness:
  - Matching different images of abstract image patterns…



Abstract Appearance Patterns

…faces, brains, places…



Why Match Abstract Appearance Patterns?

- Organizing masses of image data
  - Image database indexing (Google, Microsoft)
  - Visual mapping, image-based localization
- Detection
  - Faces, people, terrorists
- Description
  - Anatomical study and analysis, i.e. the human brain.

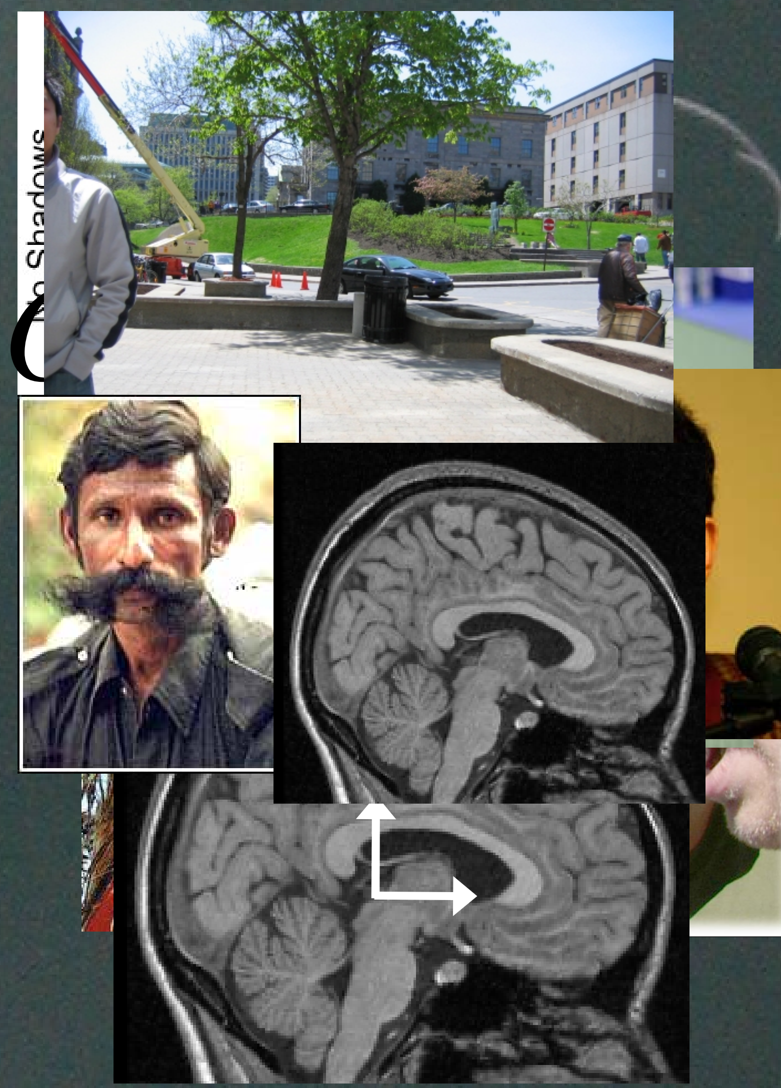
How to Match/Detect Abstract Appearance Patterns?

- Learn an appearance model or description from many pattern instances
  - Probabilistic modeling
  - Statistical parameter estimation
  - Machine learning

From what I've seen, a
face has eyes,
sometimes they're
covered by sunglasses,
…

Why Are Abstract Patterns Difficult To Model?

1) Illumination change.
2) Geometrical deformation.
3) General, different pattern types.
4) Computational efficiency.
5) Partial pattern occlusion.
6) Clutter, background noise.
7) Intra-pattern variability.
8) Multi-modal pattern variability.
9) Viewpoint change.
10) Anatomical reference frames.



How Are Modeling Difficulties Handled?

1) Illumination change.
2) Geometrical deformation.
3) General, different pattern types.
4) Computational efficiency.
5) Partial pattern occlusion.
6) Clutter, background noise.
7) Intra-pattern variability.
8) Multi-modal pattern variability.
9) Viewpoint change.
10) Anatomical reference frames.

Invariant image features.

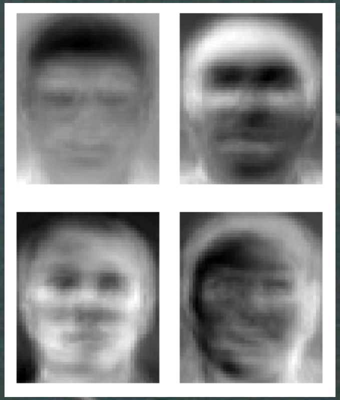
Probabilistic modelling, learning.

My research:

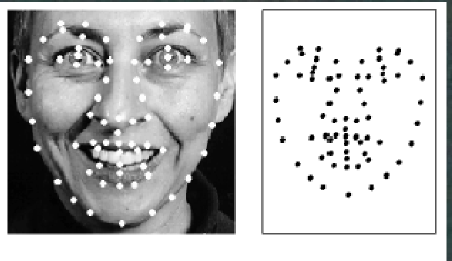
Probabilistic OCI modelling.

Global Models (no local features)

- Eigenfaces:
  - Turk & Pentland 1991
  - Linear, uni-modal multivariate Gaussian
  - Pixel intensities.



- Active Appearance Model:
  - Cootes & Taylor 1998
  - Linear, uni-modal multivariate Gaussian
  - Intensities & point geometry.

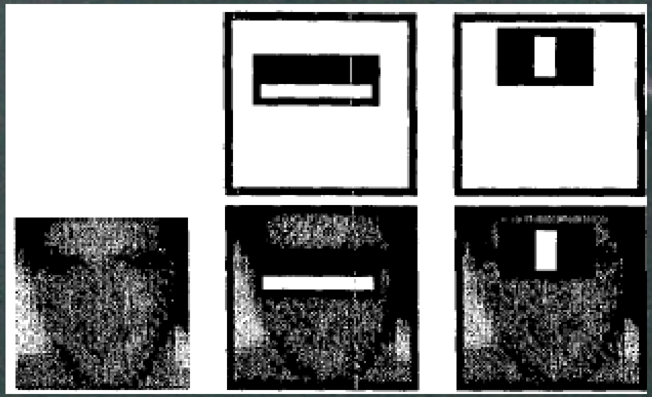


Labelled image Points

Disadvantage: cannot model local variation (i.e. a face with/without sunglasses).

Viola-Jones Model

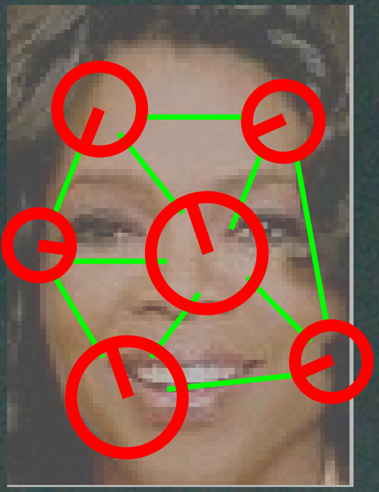
- Different kind of local feature
  - Harr wavelet, very simple
- Discriminative learning
  - Decision tree
  - Adaboost learning algorithm
- Very long learning.
- Very fast feature computation/detection.



Rapid object detection using a
boosted cascade of simple features
Jones & Viola 2001

Local Feature Models

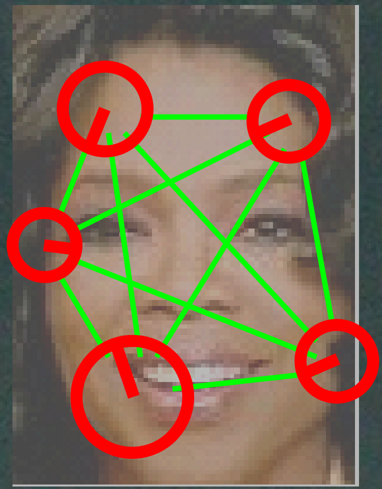
- 2D feature configurations
  - Feature appearances independent given geometry
    - Modeled locally, i.e. Gaussian/eigenface
  - Geometrical dependence varies.



Fully-Connected

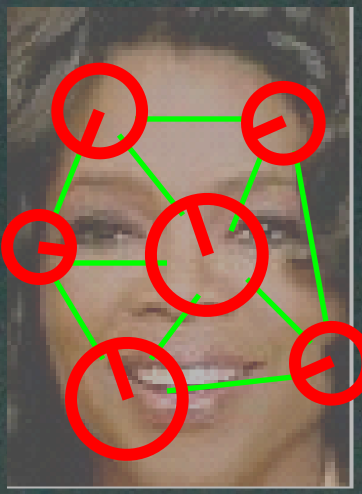
- All feature geometries related
  - ‘constellation model’.
  - $O(N^2)$ modeling complexity.

Weber & Perona 2000
Fergus & Zisserman 2003



Markov

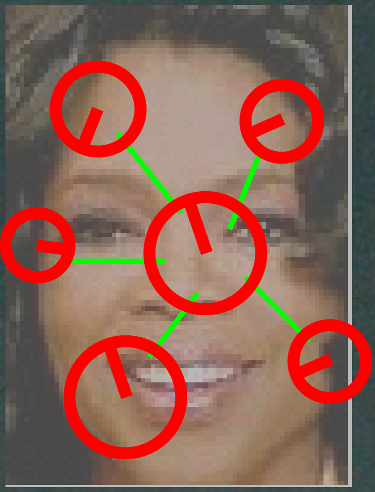
- Markov assumption
  - Local/neighbourhood dependencies.
  - O(KN) modeling complexity, K is neighbourhood size.
  - Markov random field (Geman & Geman).



Carneiro & Lowe 2006

Naïve-Bayes

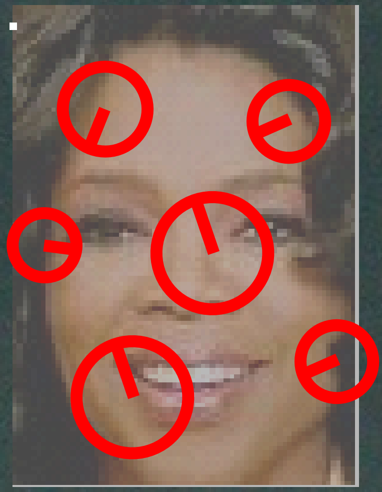
- All feature geometries independent given one 'parent' geometry.
  - 'fragment model', 'star model'
  - O(N) modeling complexity



Bart & Ullman 2004
Fergus & Zisserman 2005

Independent

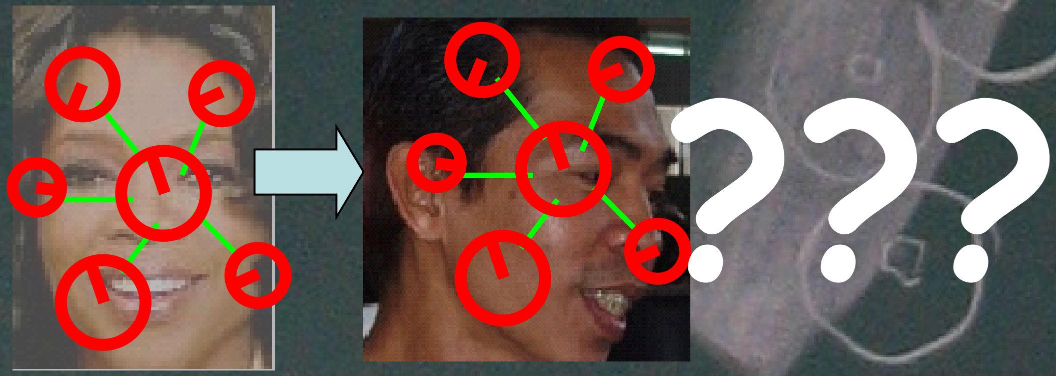
- Geometry free
  - 'bag-of-features model'
  - Consider only feature appearance and occurrence, less complicated.
  - Cannot say anything about pattern geometry.



Sivic & Zisserman 2005
Dorko & Schmid 2003.

Local Feature Models & Viewpoint

- 2D feature configurations
  - Inherently single viewpoint.
- Do not represent 3D object/scene appearance over viewpoint change
  - Features disappear, new features appear.
  - Inter-feature geometrical relationships change.



Viewpoint-invariant Modeling

- Goal:
  - Model 3D object class appearance in terms of 2D image features.
  - Learn model from natural, cluttered images.
  - Detect 3D object class instances from arbitrary viewpoints.

*** Detection Over Viewpoint via the Object Class Invariant**
Toews, Arbel, Int'l Conf. on Pattern Recognition, 2006.

*** A Statistical Parts-based Appearance Model of Anatomical Variability**
Toews, Arbel, IEEE Trans. on Medical Imaging, Special Issue on Computational Neuroanatomy, *In Press*, 2007.

*** A Statistical Parts-based Appearance Model of Intersubject Variability**
Toews, Collins, Arbel, Int'l Conf. on Medical Image Computing and Computer Aided Intervention, 2006.

Viewpoint-invariant Modeling

- Other approaches:
  - Battery of single viewpoint detectors
    - Difficult to learn, training images sorted according to viewpoint.
  - Aspect graphs, appearance manifolds
    - Do not address occlusion or multimodal appearance.
- No notion of object identity over viewpoint.

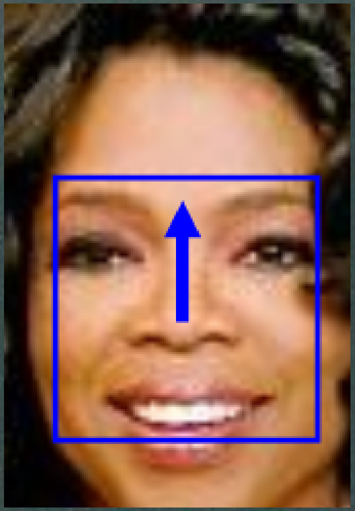
Object Class Invariant Model

- Consider features relative to a reference frame that is:
  1) Uniquely defined in each pattern/object class instance.
  2) Invariant to the geometrical transform arising the imaging process (i.e. projective xform).

Object Class Invariant

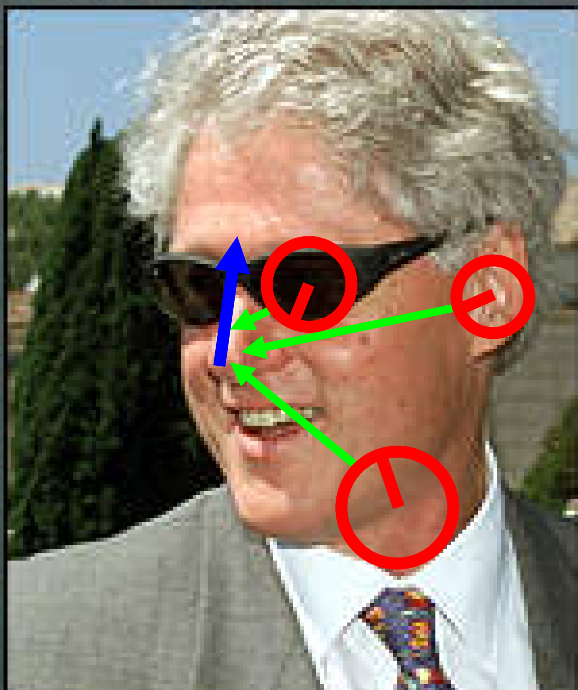
Local Feature Models & Viewpoint

- Projective transform
  - 8 parameter geometric transform.
  - Describes the appearance of a 3D plane in the presence of viewpoint change.



Note: lines are preserved, squares are not!

OCI Model Components



Object Class Invariant

$o = \{o^b, o^g\}$

Occurrence: binary presence or absence.

Geometry: location, scale, orientation.

Scale-invariant Feature

$m_i = \{m_i^b, m_i^g, m_i^a\}$

Appearance: derivative histograms.
Note: the OCI is unobservable, and has no appearance!

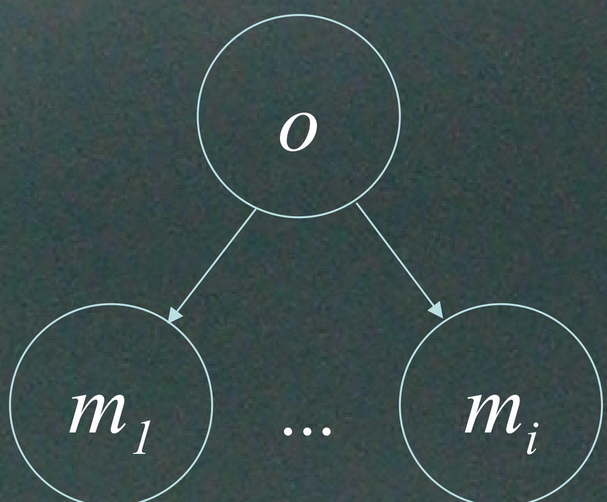
Transform relating feature and OCI geometries:

$t_i : m_i^g \to o^g, o^g = t_i(m_i^g)$

OCI Model Formulation

- Features independent given OCI

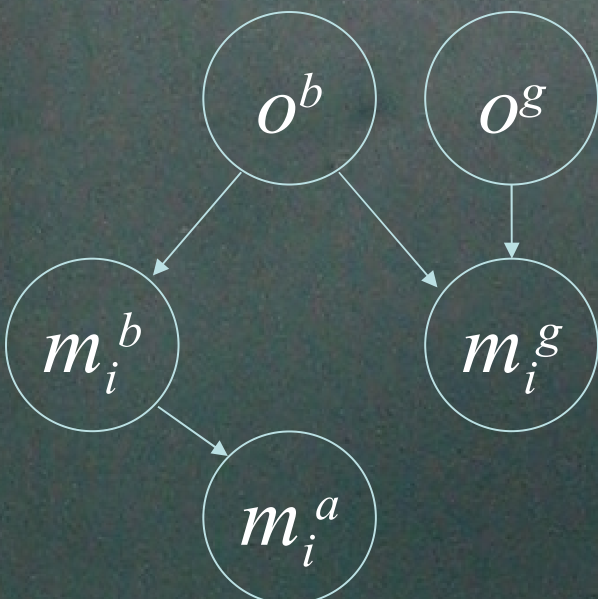
$$p(o \mid \{m_i\}) = \frac{p(\{m_i\} \mid o)\, p(o)}{p(\{m_i\})} = \frac{p(o)}{p(\{m_i\})} \prod_i p(m_i \mid o)$$



Meaning: Once the OCI geometry is known, the remaining feature variability can be quantified independently or locally.

OCI Model Formulation

- Focus on feature/OCI term $p(m_i|o)$



$$p(m_i \mid o) = p(m_i^a, m_i^b \mid o)\, p(m_i^g \mid o)$$
$$= p(m_i^a \mid m_i^b)\, p(m_i^b \mid o^b)\, p(m_i^g \mid o^b, o^g).$$

$p(m_i^a \mid m_i^b)$

Feature appearance given presence.

Monotonic distribution: Gaussian.

$p(m_i^b \mid o^b)$

Feature presence given OCI presence.

Binomial probability.

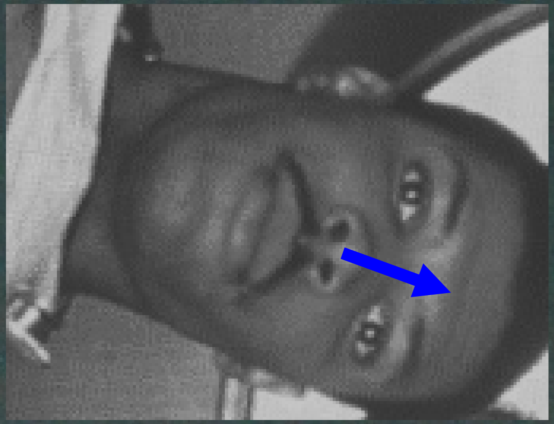
$p(m_i^g \mid o^b, o^g)$

Feature geometry given OCI geometry.

Residual error of transform from feature to OCI geometry: Gaussian.

OCI Model Learning

- Image data
  - Natural images, clutter, variation in viewpoint.
  - Labeled OCIs (approximate).
  - Automatically extracted features
    - SIFT features, Lowe 2004.


OCI Model Learning

- Identify clusters of features that:
  - Agree in geometry relative to OCI.
  - Agree in appearance.
- Each cluster is a model part m_i
  - Estimate distribution parameters.

$$p(m_i^a \mid m_i^b) \quad p(m_i^b \mid o^b) \qquad p(m_i^g \mid o^b, o^g)$$

Geometrical Agreement

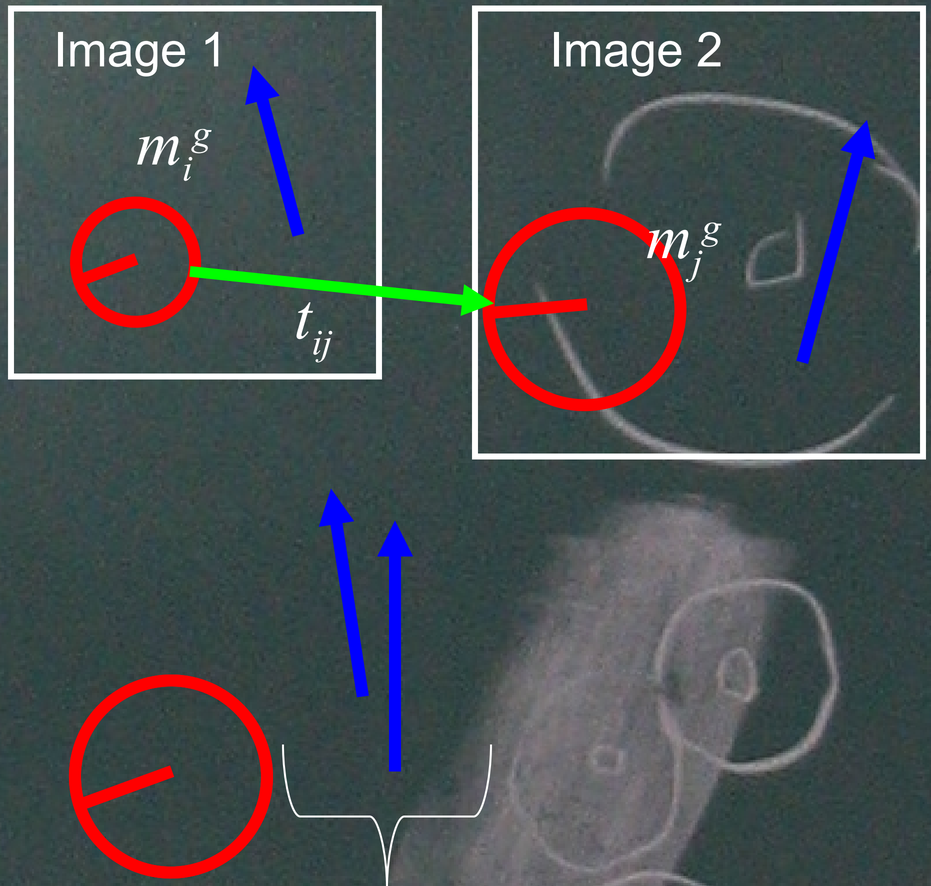
Purpose: measure geometrical similarity between features m_i and m_j.

1) Determine transform t_{ij} aligning feature geometries m_i^g and m_j^g.

$$t_{ij} : m_i^g \rightarrow m_j^g, m_j^g = t_{ij}(m_i^g)$$

2) Transform geometry m_i^g & associated OCI.

3) Measure discrepancy in OCI geometries.

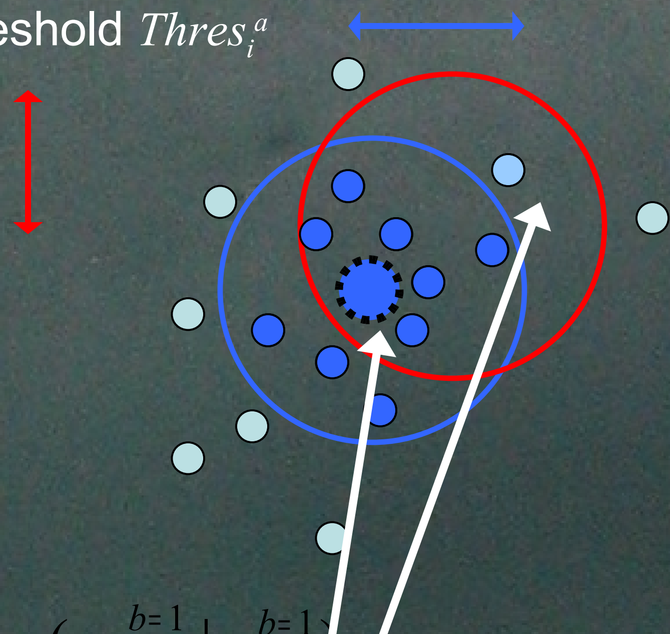


OCI geometrical error: scale, orientation, translation relative to OCI scale.

OCI Model Learning

OCI localization error threshold $Thres^g$

Appearance threshold $Thres_i^a$



$$\frac{p(m_i^{b=1} \mid o^{b=1})}{p(m_i^{b=1} \mid o^{b=0})}$$

Feature space: appearance & geometry

For each feature:

1) Geometric clustering: Identify features that, when matched, agree on location of OCI ($Thres^g$).

$$p(m_i^g \mid o^b, o^g)$$

2) Appearance clustering: Determine appearance variance ($Thres_i^a$) such that ratio of true to false matches is maximized.

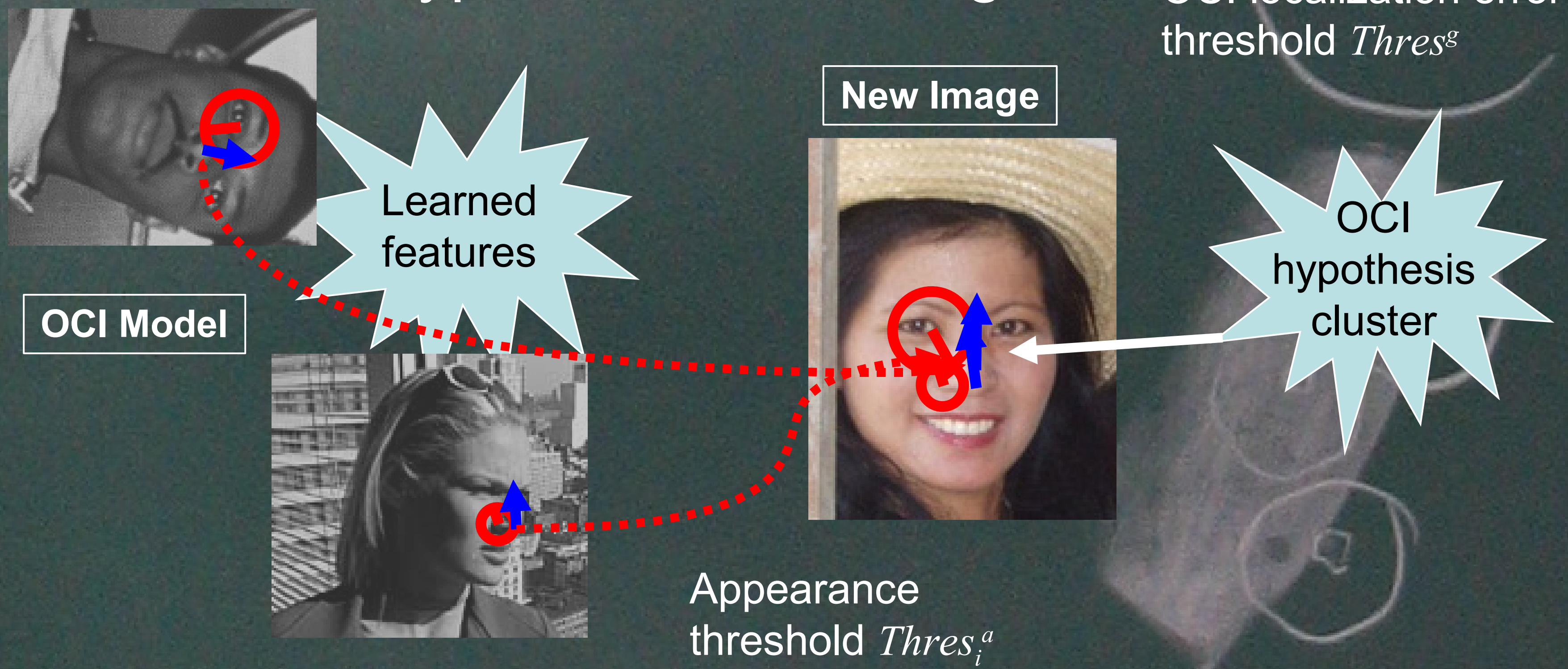
$$p(m_i^a \mid m_i^b)$$

$$p(m_i^b \mid o^b)$$

Discard redundant features.

OCI Model: Fitting

- Identify OCI instances in new image
  - Probabilistic voting technique.
  - Robust hypothesis clustering.



OCI Model: Fitting

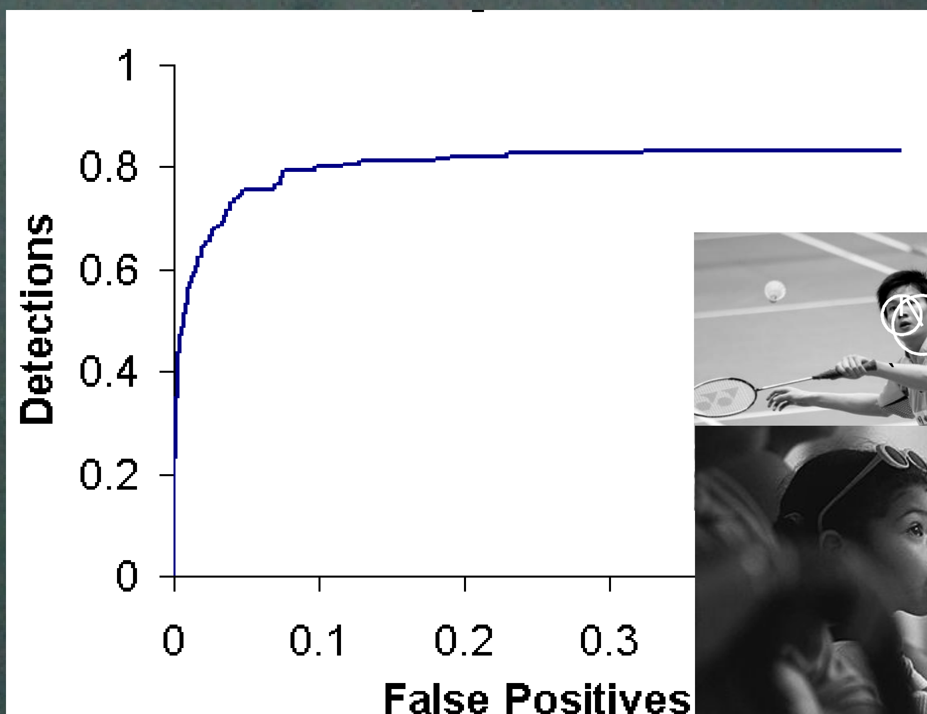
- OCI hypothesis cluster quality
  - Bayesian decision rule

$$\gamma(o^g) = \frac{p(o^{b=1}, o^g \mid \{m_i\})}{p(o^{b=0}, o^g \mid \{m_i\})} = \frac{p(o^{b=1}, o^g)}{p(o^{b=0}, o^g)} \prod_i \frac{p(m_i \mid o^{b=1}, o^g)}{p(m_i \mid o^{b=0}, o^g)}.$$

Viewpoint-invariant Detection

- Validation: face detection

  180 cluttered images, arbitrary viewpoints, leave-one-out detection.



Other Issues

- Unsupervised OCI model learning
  - No labeling.
- Different OCIs
  - Line segment, sphere, point.
- Other learning tasks
  - Learn pattern traits, i.e. gender, age

Summary

- What?
  - Abstract patterns and object classes.
- How?
  - Learn appearance patterns from many examples.
  - Probabilistic modeling of invariant features.
- Object Class Invariant modeling
  - Appearance patterns over viewpoint change.