

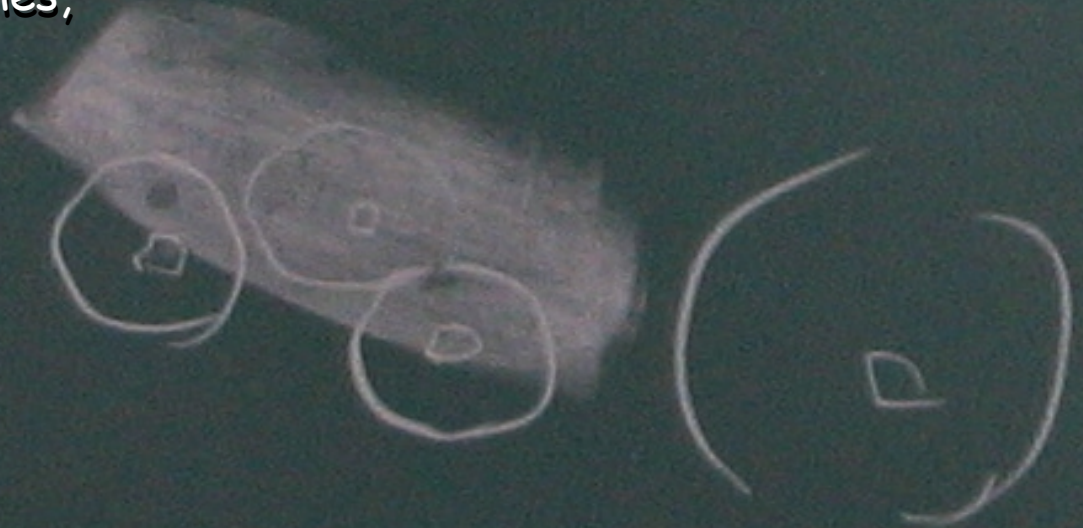
Modeling Appearance Patterns in Image Sets

Matthew Toews, PhD Candidate

Centre for Intelligent Machines,

McGill University

January, 2007



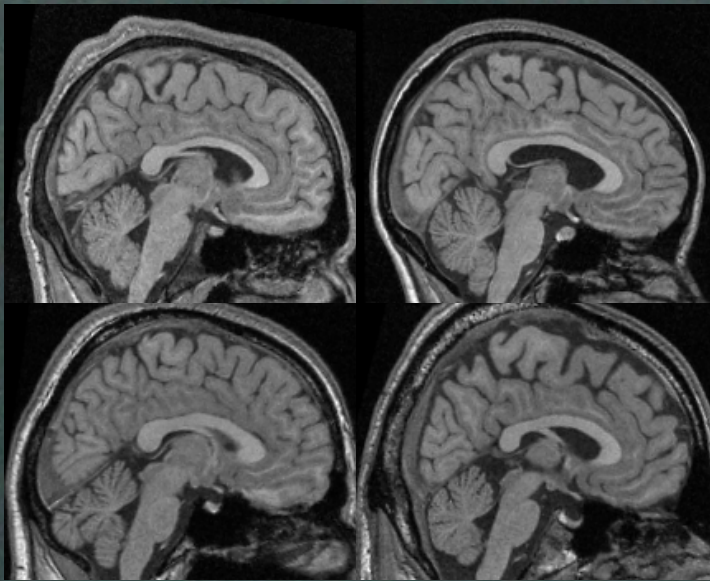
Overview

- Pattern Appearance Modeling
 - Problem statement & issues
 - Local invariant features
 - Probabilistic modeling
- Our Approach
 - Object class invariant model
 - Viewpoint invariant detection (faces)
 - Anatomical modeling (brains)
- Future



What Are Appearance Patterns?

- General, abstract image patterns
 - faces, brains, places...



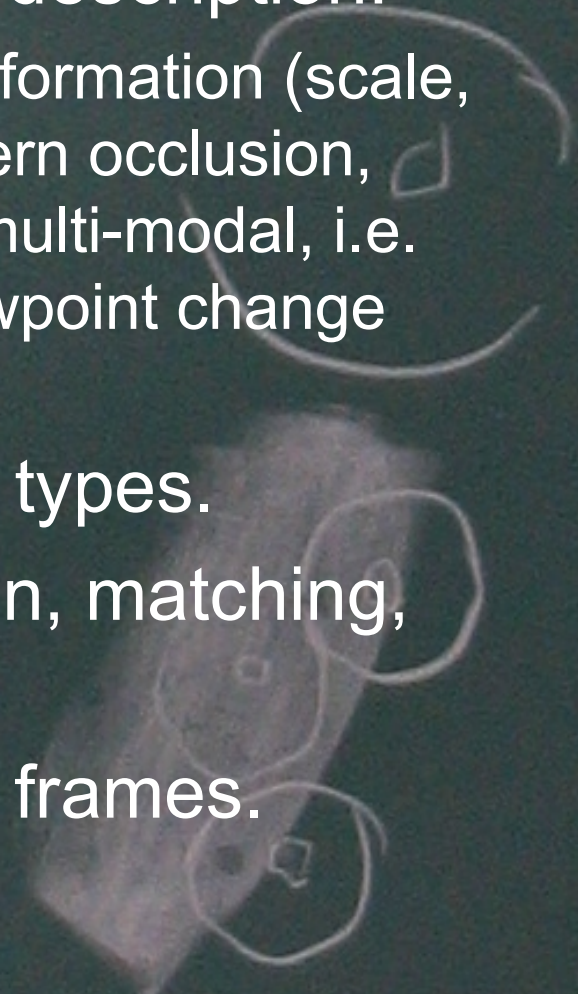
Why Learn Appearance Patterns?

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



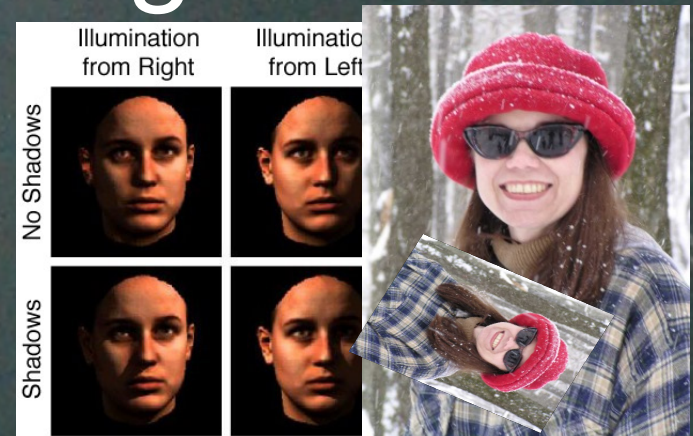
Why Difficult?

- Factors complicating appearance description:
 - Illumination change, geometrical deformation (scale, orientation, translation), partial pattern occlusion, intra-pattern variability (potentially multi-modal, i.e. faces with/without sunglasses), viewpoint change (3D object classes).
- Generality, many different pattern types.
- Computational efficiency: detection, matching, learning, inference.
- Anatomical description, reference frames.



Appearance Modeling: Issues

- 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.



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Local,
invariant
image
features.

Probabilistic
modelling,
learning.

Our research:
OCl modelling.



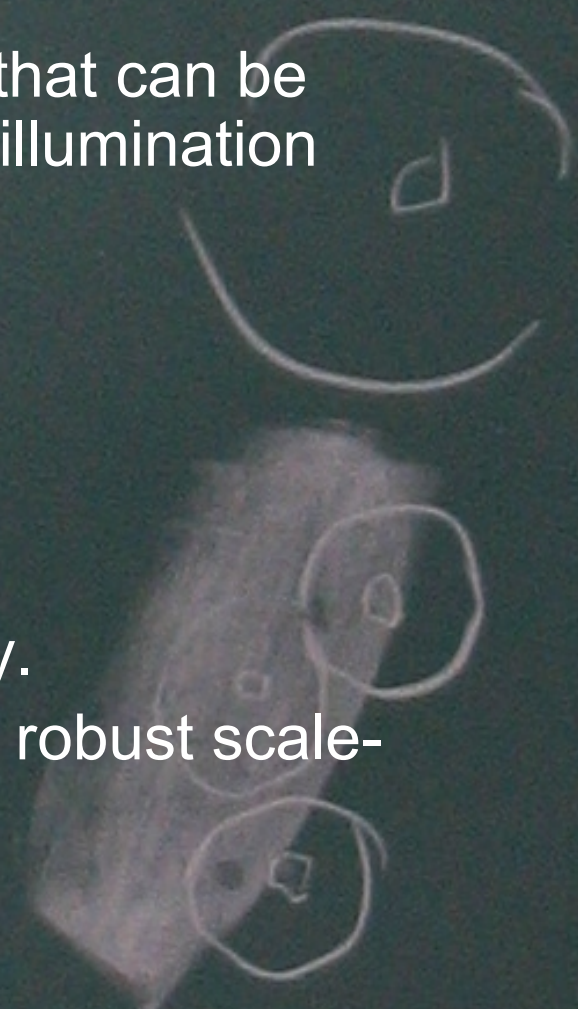
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Local Invariant Features

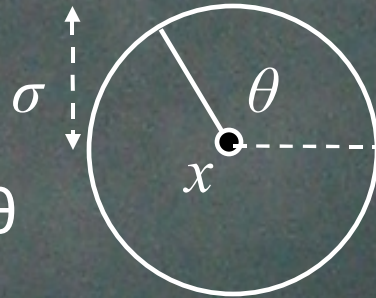
- Idea:
 - Consider informative image regions that can be robustly detected in the presence of illumination change and geometric deformation.
 - Interest points, salient regions, etc.
- Literature:
 - Moravec 1970s: interest points.
 - Harris 1980s: corner detectors.
 - Lindeberg 1990s: scale-space theory.
 - Lowe, Schmid 1990-2000s: efficient, robust scale-invariant feature detectors.



Local Invariant Features

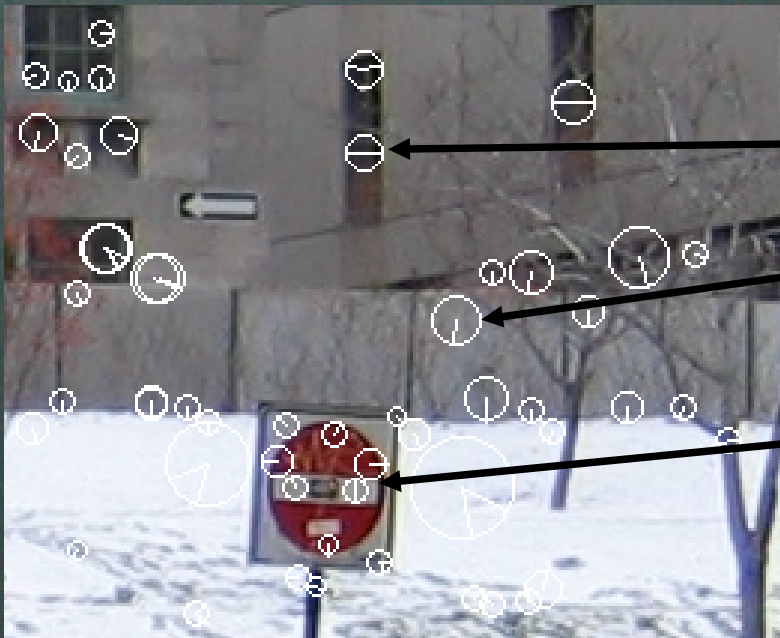
Geometry

- Location x
- Orientation θ
- Scale σ



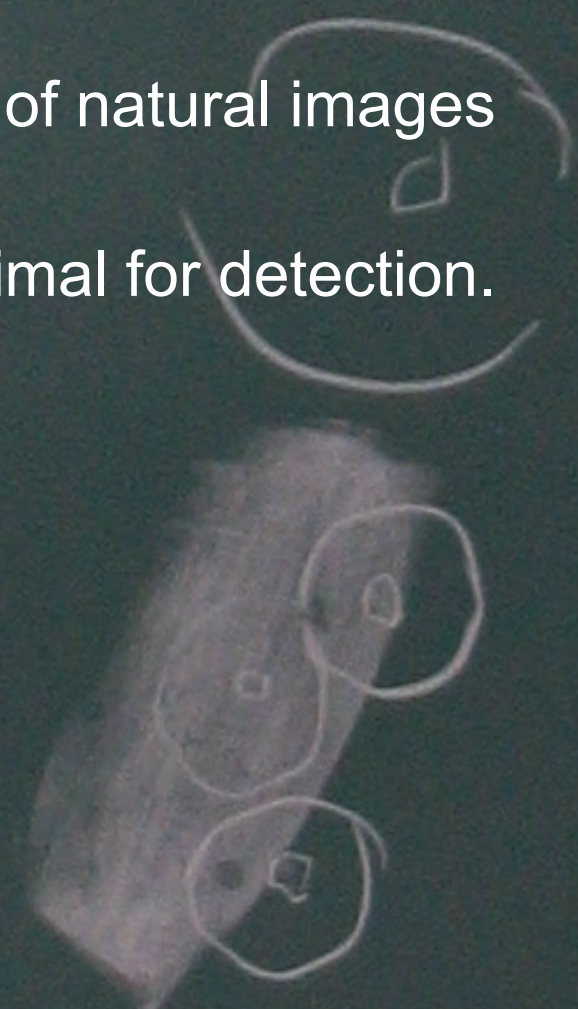
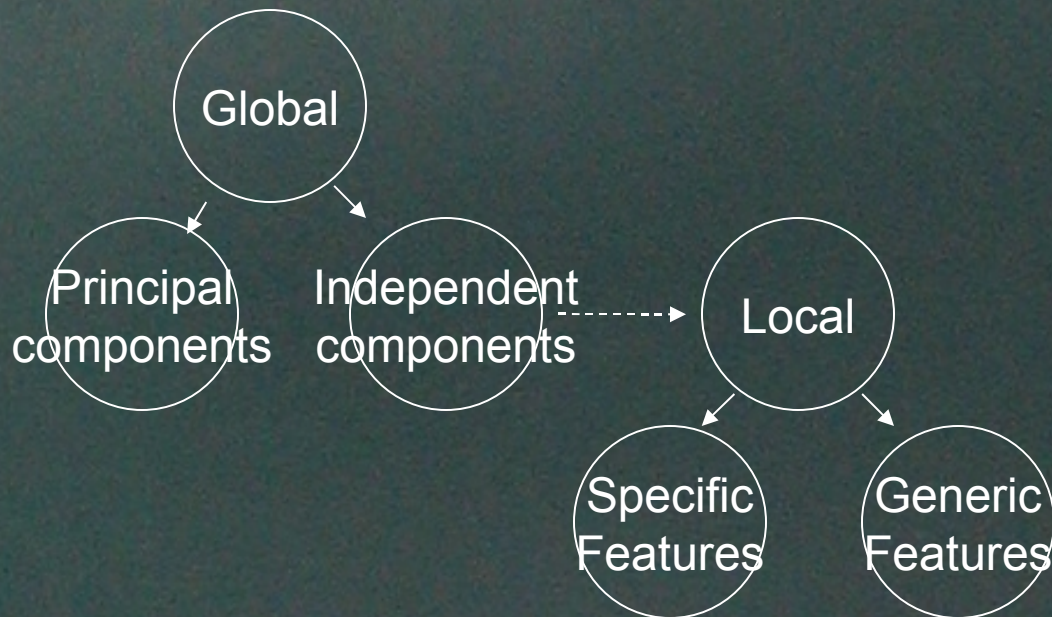
Appearance

- Image intensity information
- I.e. Pixels, edges

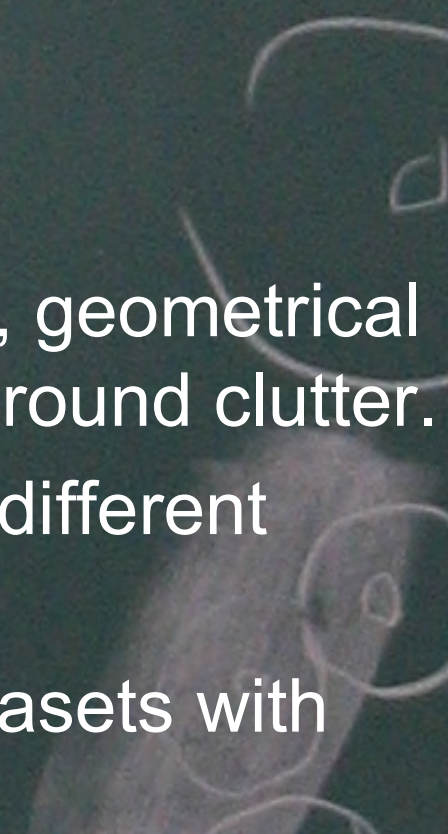


Local Invariant Features

- Local vs. global features
 - Bell 1997: independent components of natural images are local features.
 - Ullman 2002: global features suboptimal for detection.



Local Invariant Features

- Advantages:
 - Efficient to extract and match:
 $O(N \log(N))$ time complexity.
 - Robust to illumination change, geometrical deformation, occlusion, background clutter.
 - Generally applicable to many different pattern types.
 - Allow modeling from large datasets with minimal manual supervision.
- 

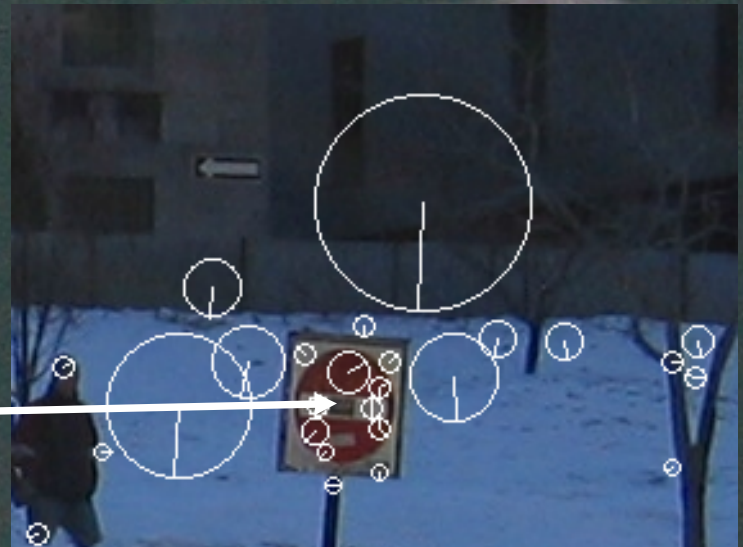
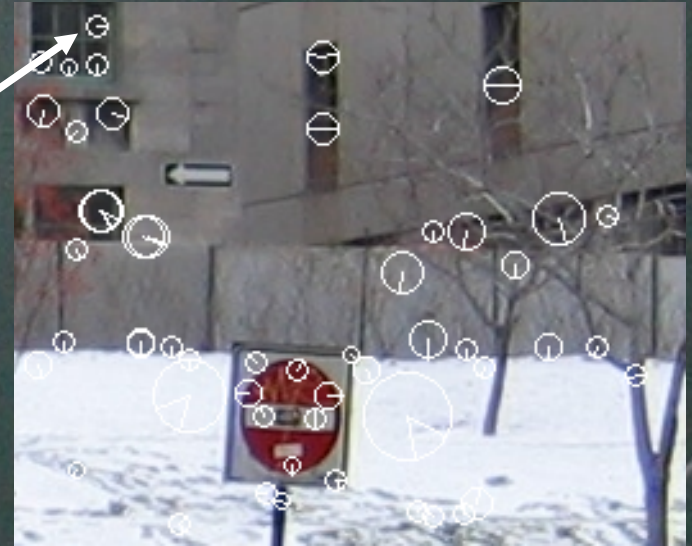
Local Invariant Features

- Difficulties:
 - Matching different instances of the same object class or abstract pattern, i.e. faces.
 - Cannot model multi-modal intra-pattern variation (faces with/out sunglasses).



Local Invariant Features

- Vary with time of day, the season.

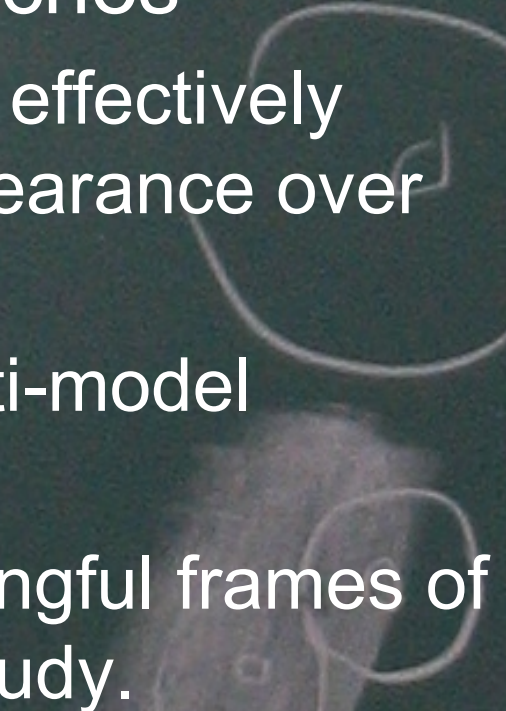


Probabilistic Modeling & Learning

- Idea:
 - Model appearance & geometric variability of object/pattern classes or categories.
 - Learn pattern appearance from image sets.
- Literature:
 - * **Global features**
Turk & Pentland 1991, Cootes & Taylor 1998
 - * **2D invariant feature configurations**
Weber & Perona 2000, Fergus & Zisserman 2003, Ullman 2004, Crandall & Huttenlocher 2005.
 - * **Geometry free, 'bag-of-words'**
Sivic & Zisserman 2005, Dorko & Schmid 2003.

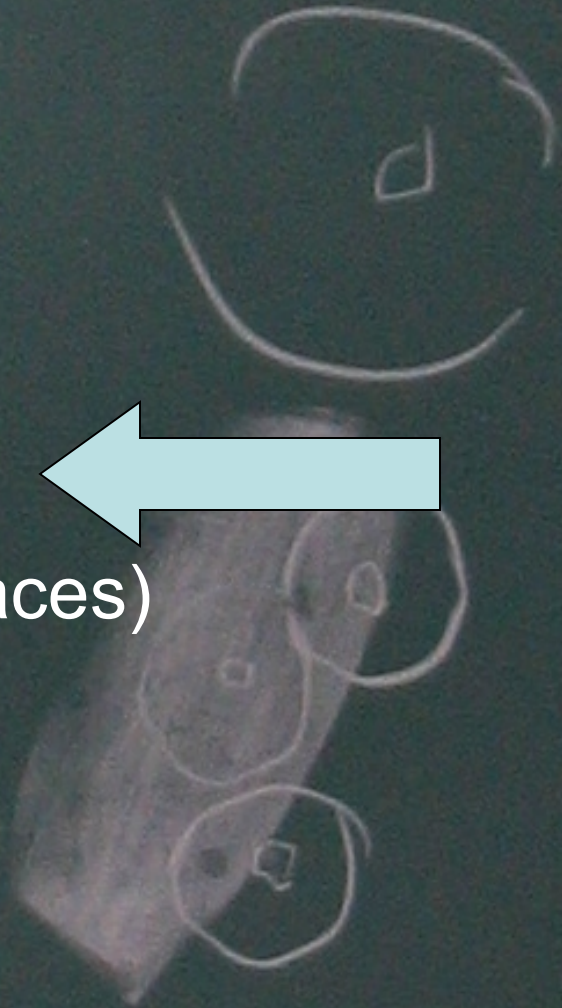


Probabilistic Modeling & Learning

- Limitations of learning approaches
 - Inherently 2D in nature, cannot effectively represent 3D object/scene appearance over viewpoint change.
 - Do not address learning of multi-model appearance patterns.
 - Do not relate features to meaningful frames of reference, i.e. for anatomical study.
- 

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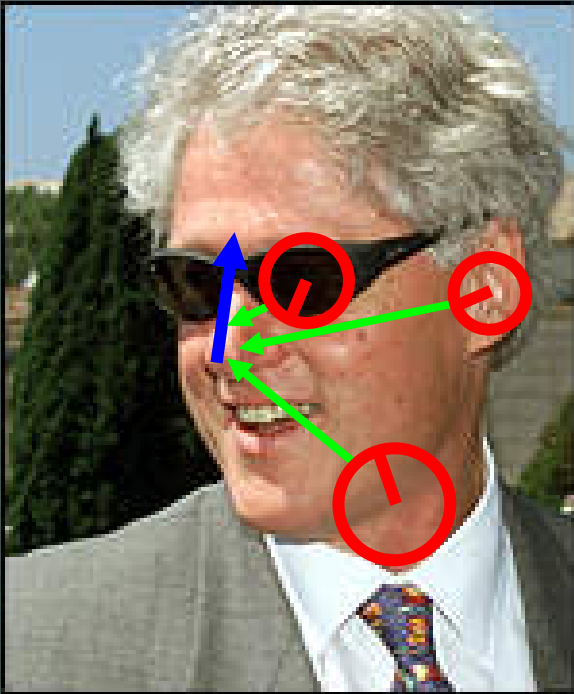


Object Class Invariant Model

- 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 from the imaging process (*projective, orthographic, ...*).
- The object class invariant.



OCI Model: Components



Object Class Invariant

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

Occurrence:
binary presence
or absence.

Geometry: location,
scale, orientation.

Scale-invariant Feature

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

Transform relating feature and
OCI geometries:

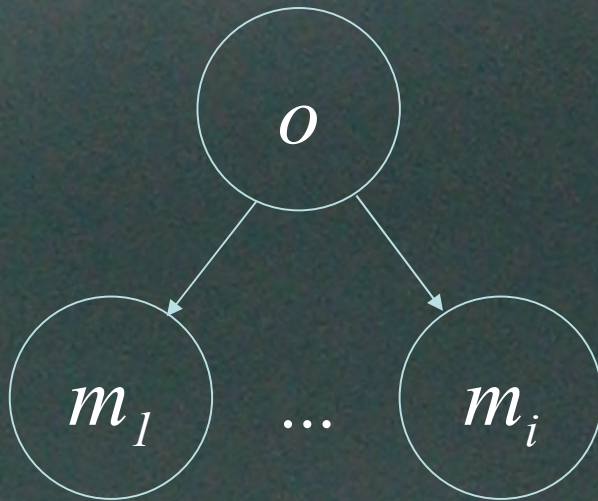
$$t_i: m_i^g \rightarrow o^g, o^g = t_i(m_i^g)$$

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

OCI Model: Formulation

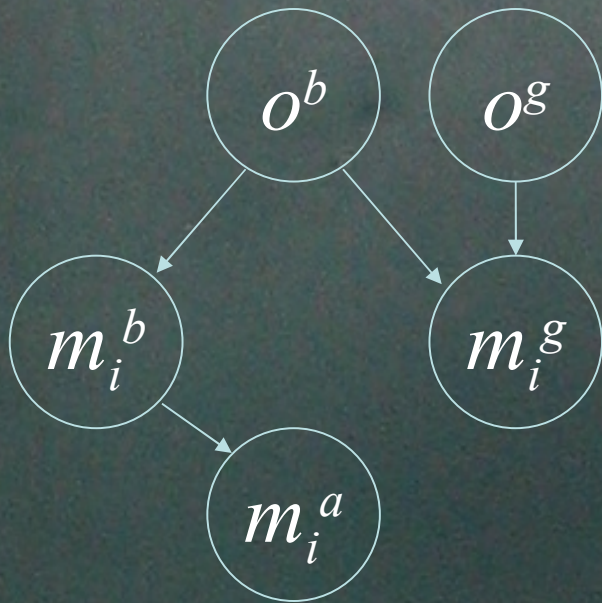
- Features independent given OCI

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



OCI Model: Formulation

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



$$\begin{aligned} p(m_i | o) &= p(m_i^a, m_i^b | o) p(m_i^g | o) \\ &= p(m_i^a | m_i^b) p(m_i^b | o^b) p(m_i^g | o^b, o^g). \end{aligned}$$

$$p(m_i^a | m_i^b)$$

Feature appearance given presence.

Monotonic distribution: Gaussian.

$$p(m_i^b | o^b)$$

Feature presence given OCI presence.


Binomial probability.

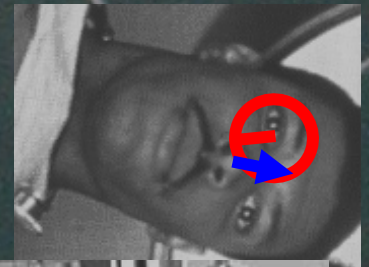
$$p(m_i^g | o^b, o^g)$$

Feature geometry given OCI geometry.

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

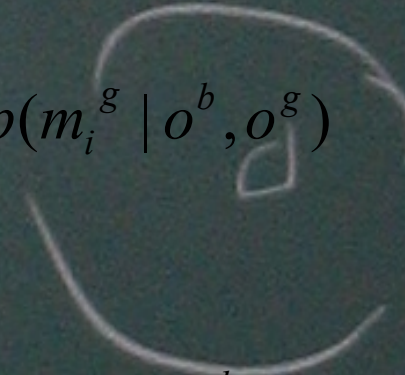
OCI Model: Learning

- Supervised learning:
 - Approximately labeled OCI 
- Large, unknown number of model features
 - EM or KMeans do not apply
- Robust clustering
 - Feature geometry relative to OCI
 - Feature appearance




OCI Model: Learning

- Feature Geometry Clustering
 - Clustered according error in predicting OCI geometry.
- Feature Appearance Clustering
 - Appearance distribution variance maximizes distinctiveness, i.e. ratio of geometrically consistent/inconsistent correspondences.
- Redundancy
 - Discard redundant features.


$$p(m_i^g | o^b, o^g)$$

$$p(m_i^a | m_i^b)$$


$$p(m_i^b | o^b)$$

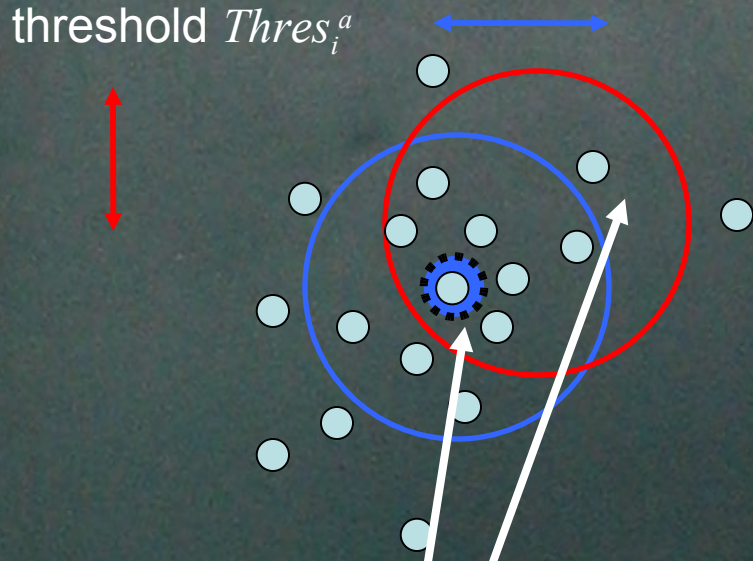
OCI Model: Learning

OCI localization error threshold $Thres^g$

Feature space: appearance & geometry

For each feature:

Appearance threshold $Thres_i^a$



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

$$p(m_i^g | o^b, o^g)$$

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

$$p(m_i^a | m_i^b)$$

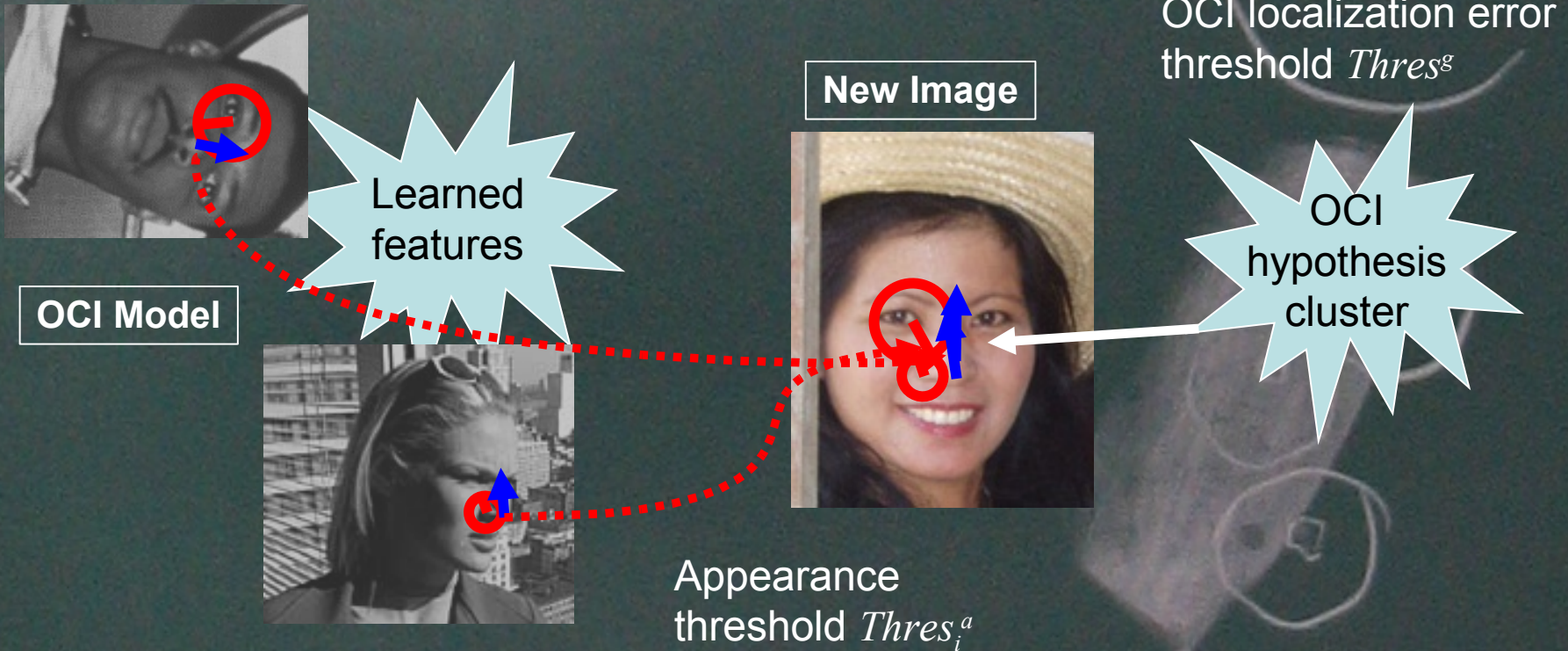
Discard redundant features.

$$p(m_i^b | o^b)$$

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

OCI Model: Fitting

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



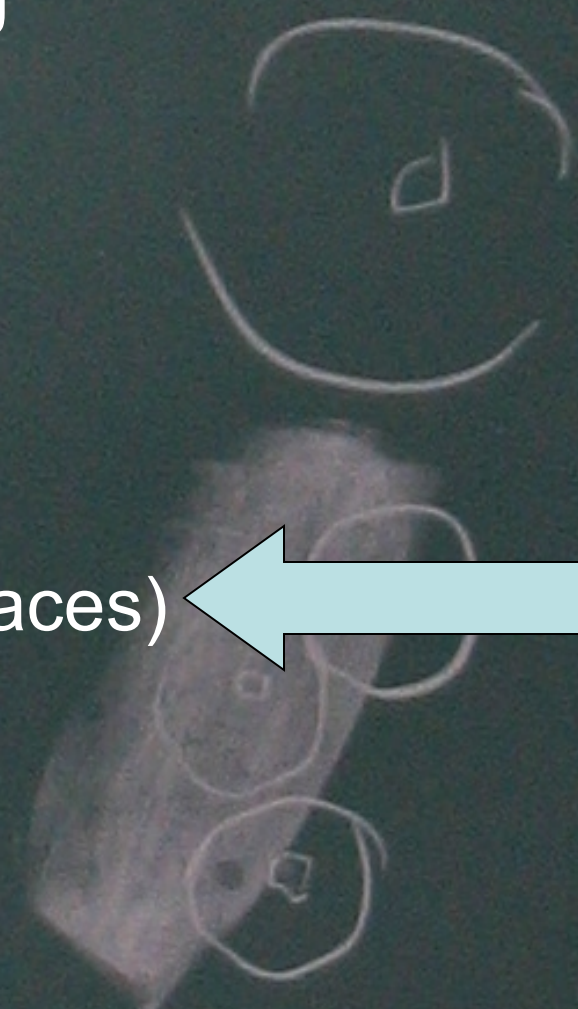
OCI Model: Fitting

- OCI hypothesis cluster quality
 - Bayesian decision rule

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

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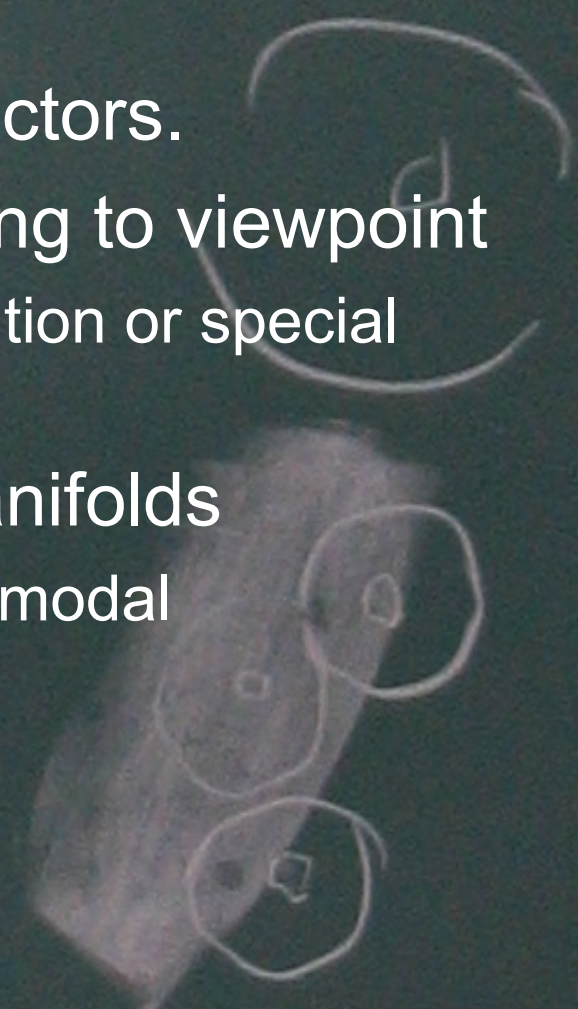
Viewpoint-invariant Detection

- Problem:
 - Learn a 3D object class appearance description in terms of 2D image features.
 - Detect 3D object class instances from arbitrary viewpoints.
- Difficulties:
 - Arbitrary images: clutter, noise, occlusion, multimodal variability, and **viewpoint change**.

Detection Over Viewpoint via the Object Class Invariant.
Toews, Matthew and Arbel, T.
International Conference on Pattern Recognition, 2006.

Viewpoint-invariant Detection

- Other approaches:
 - Battery of single viewpoint detectors.
 - Training images sorted according to viewpoint
 - Requires tedious manual intervention or special purpose hardware.
 - Aspect graphs, appearance manifolds
 - Do not address occlusion or multimodal appearance.



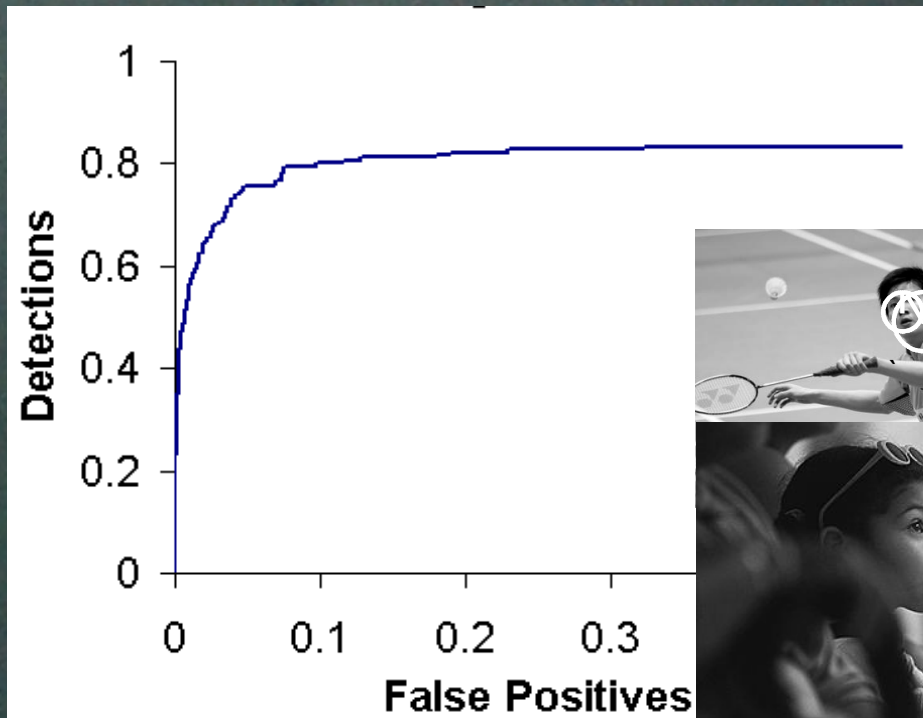
Viewpoint-invariant Detection

- Solution:
 - OCI invariant to perspective camera projection.
 - Possible OCIs: line segment, sphere, point.



Viewpoint-invariant Detection

- **Validation: face detection**
180 cluttered images, arbitrary viewpoints, leave-one-out detection.



Overview

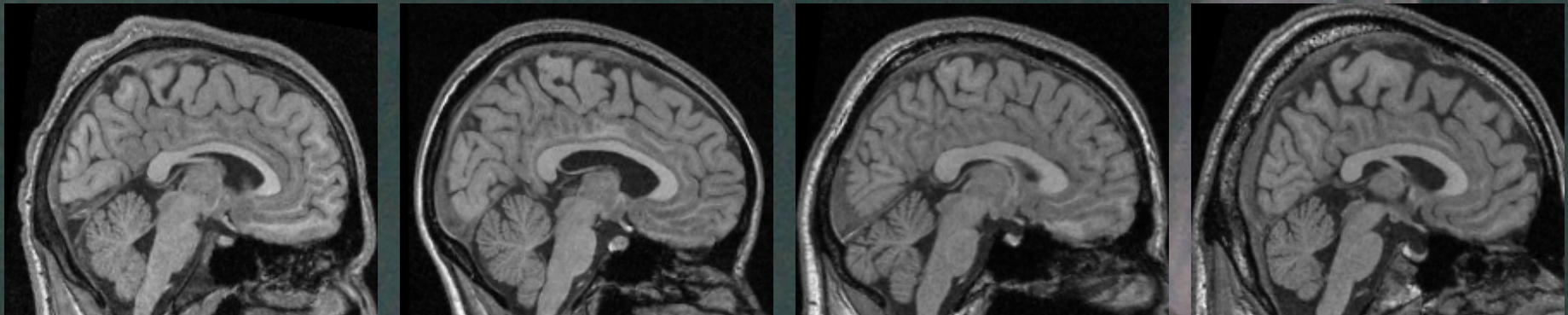
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Anatomical Modeling

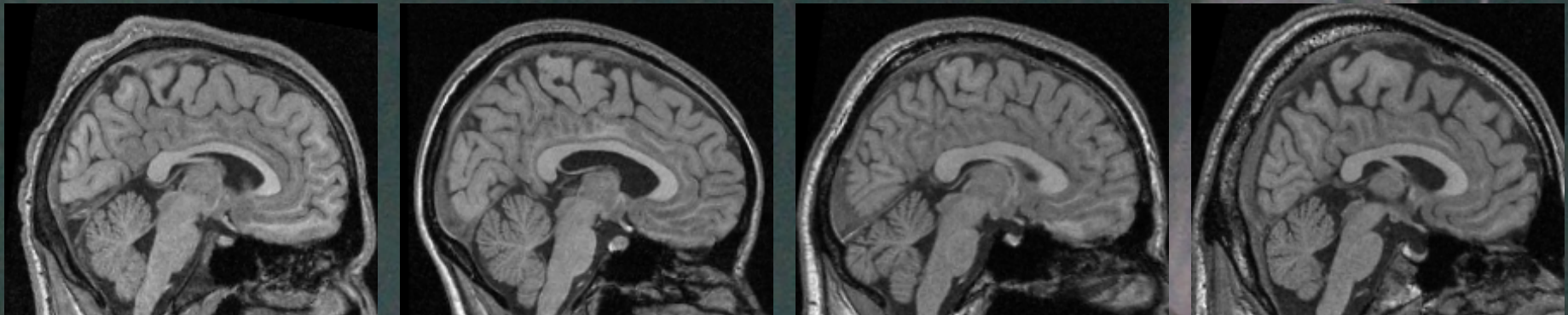
- Problem:

- Automatically learn an anatomical description from a large database of subjects (i.e. MR brain images).
- Which anatomical structures are common or rare in a population?
- How do structures vary in appearance and geometry?



Anatomical Modeling

- Challenges:
 - Learning with minimal manual supervision.
 - Robust fitting to new subjects in the presence of inter-subject variability, occlusion.
 - Identify and quantify anatomical structure in a meaningful way, i.e. with respect to a neuroanatomical reference frame.



Anatomical Modeling

- Solution:
 - Model appearance and geometry of invariant features relative to a standard neuroanatomical reference frame.
 - OCI invariant to orthographic projection from MR scanner.

A Statistical Parts-based Appearance Model of Anatomical Variability.

Toews, Matthew and Arbel, Tal.

IEEE Trans. on Medical Imaging, Special Issue on Computational Neuroanatomy, *In Press*, 2006.

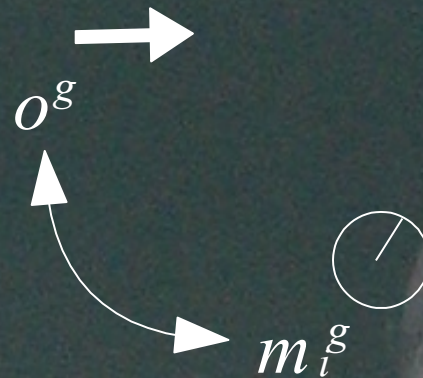
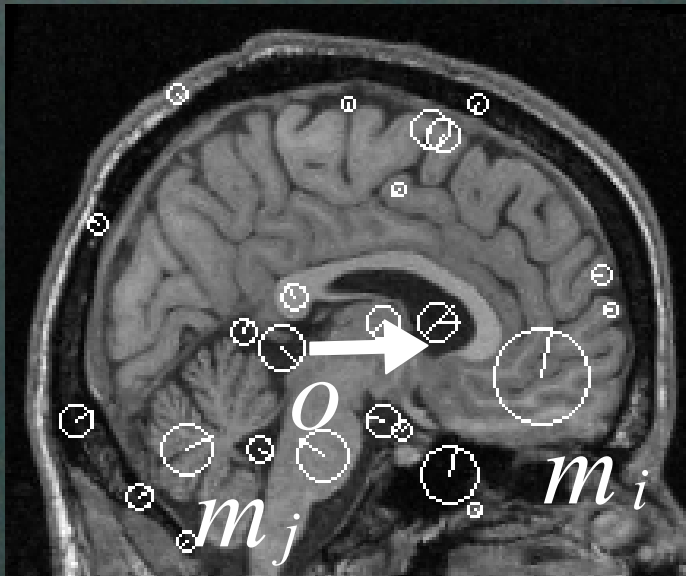
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Toews, Matthew and Collins, Louis D. and Arbel, Tal.

Int'l Conf. on Medical Image Computing and Computer Aided Intervention, 2006.

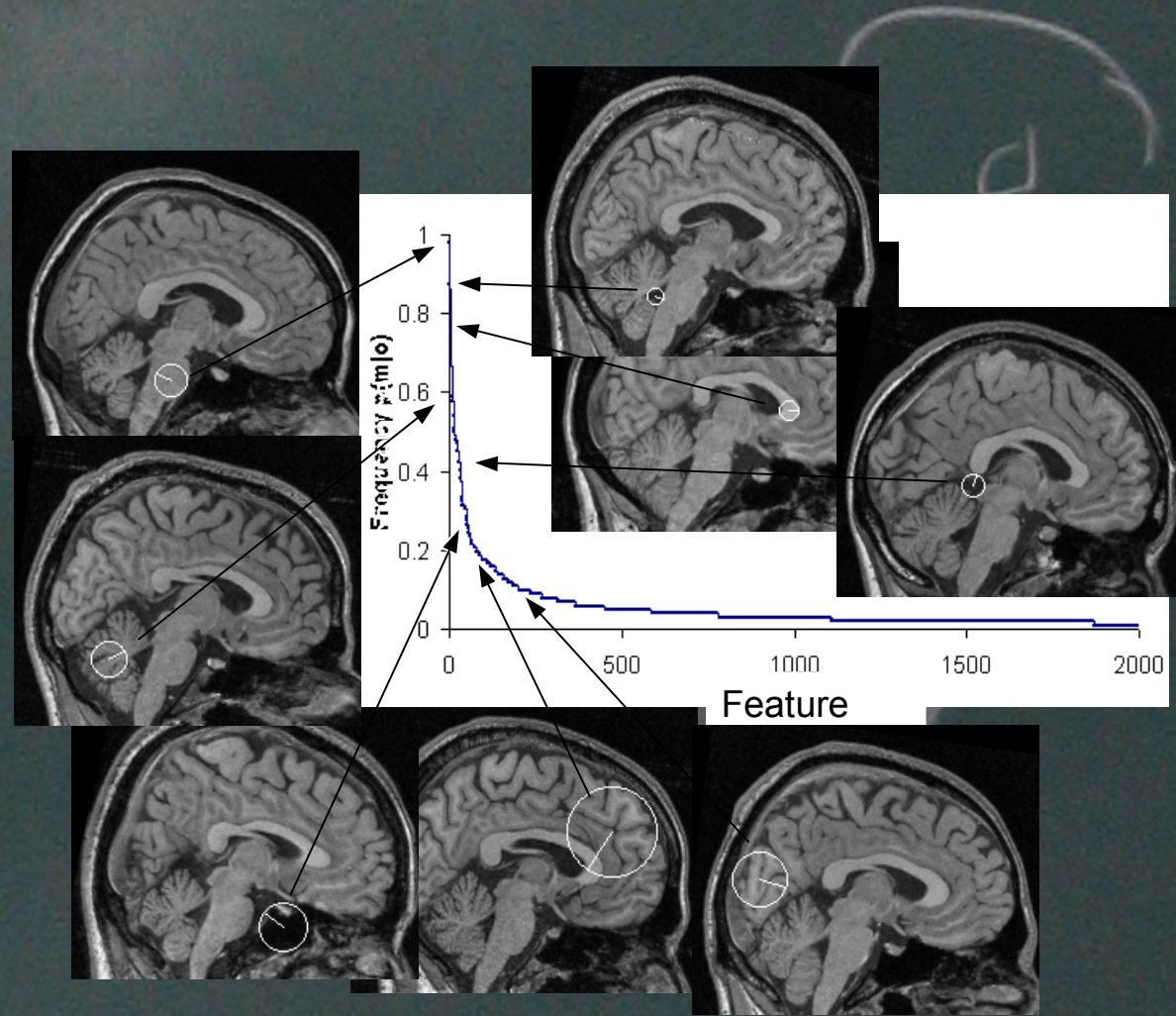
Anatomical Modeling

- Talairach neuroanatomical reference frame (Talairach 1988).
 - Mid-sagittal plane, line segment from anterior to posterior commissure.



Model Learning

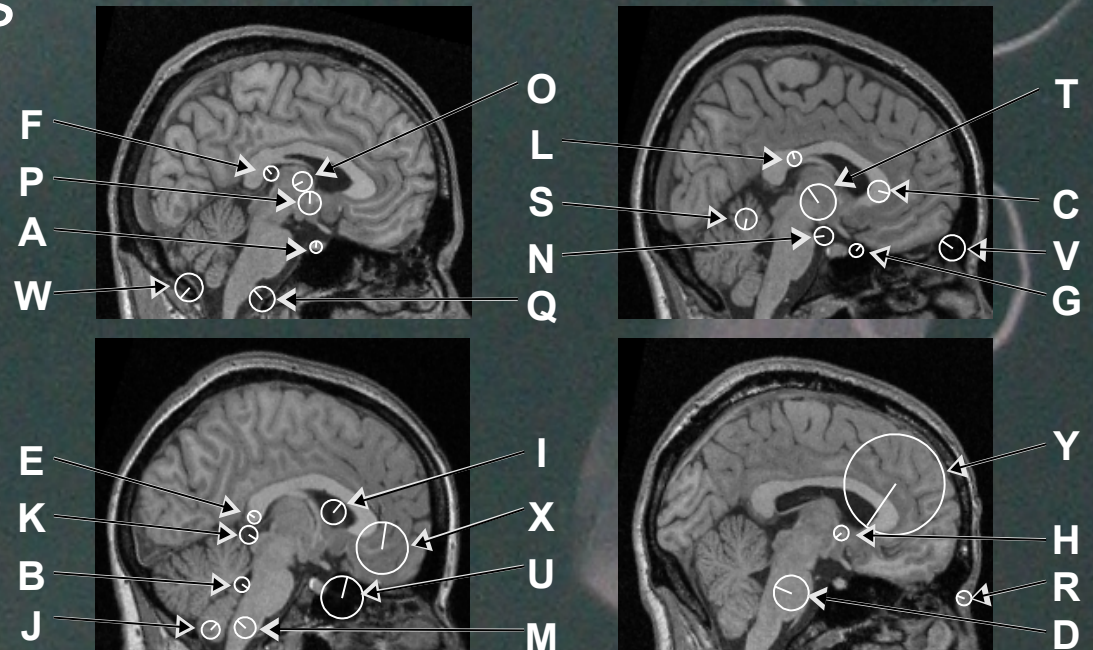
- Learning
 - Sagittal slices from 102 different brains (ICBM 152 dataset).
 - Automatic OCI labeling via approximate linear registration.



Model Fitting Error

- Quantitative evaluation
 - 50 new testing images
 - 25 model parts
 - 3 human raters

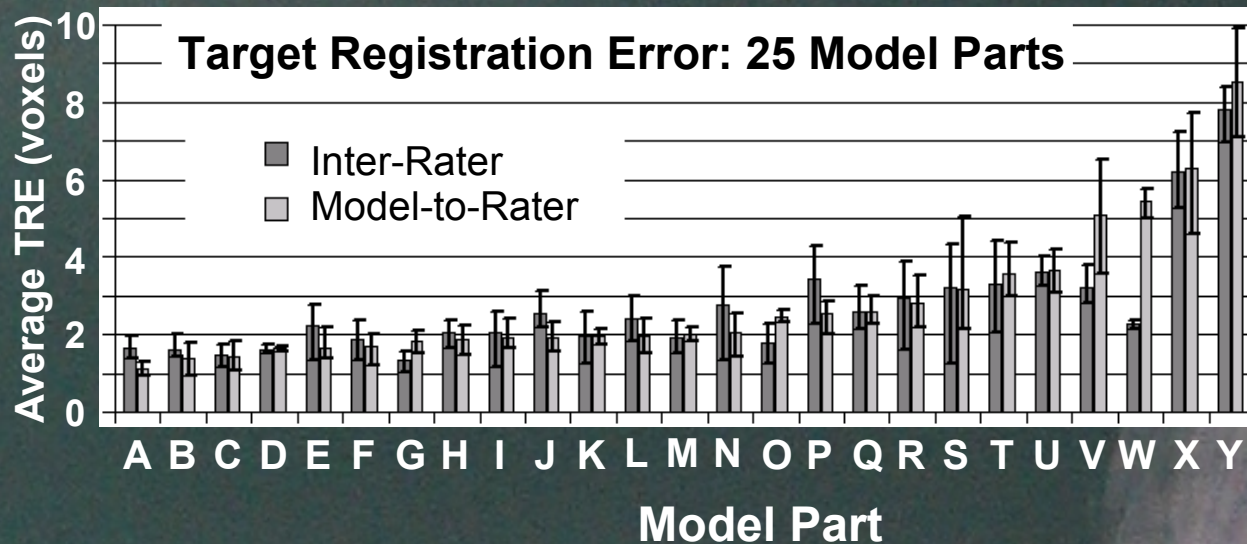
25 Test Parts



Model Fitting Error

- Fitting error is similar to human error by target registration error (TRE) measure.

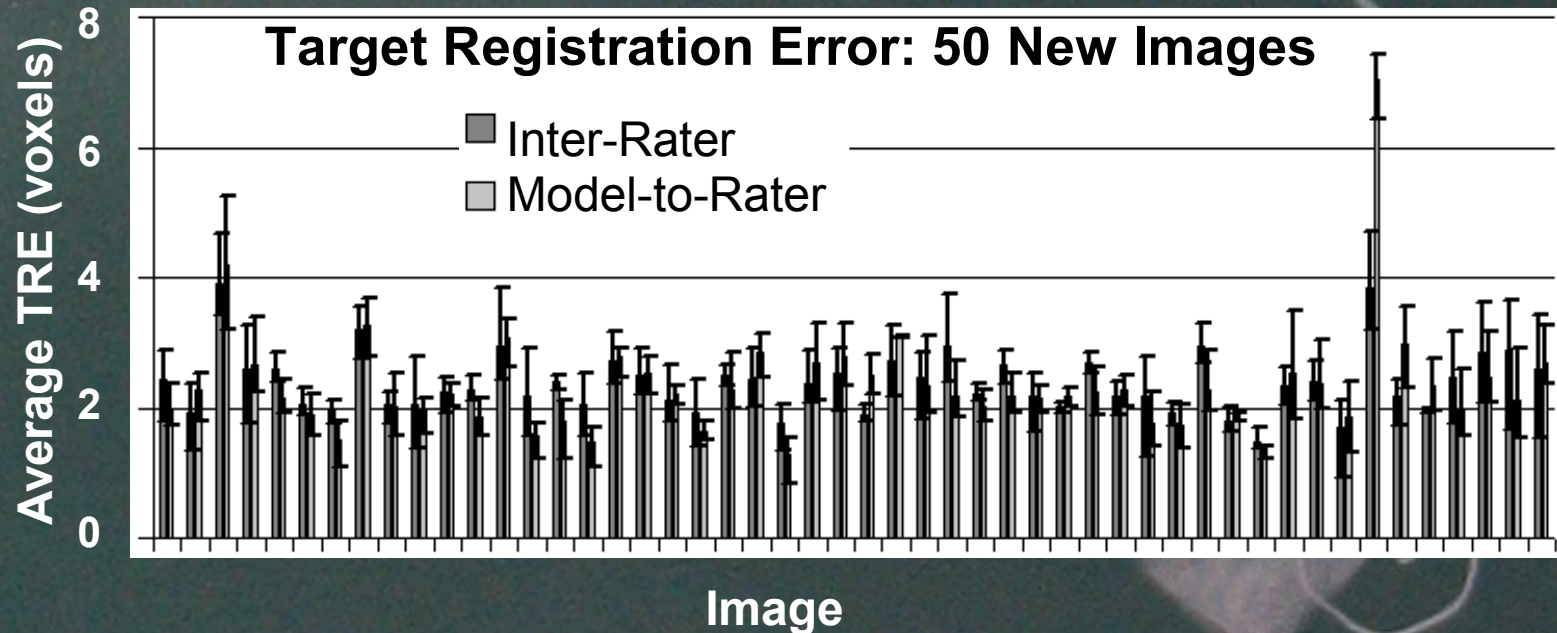
Fitting Error Per Model Part



Model Fitting Error

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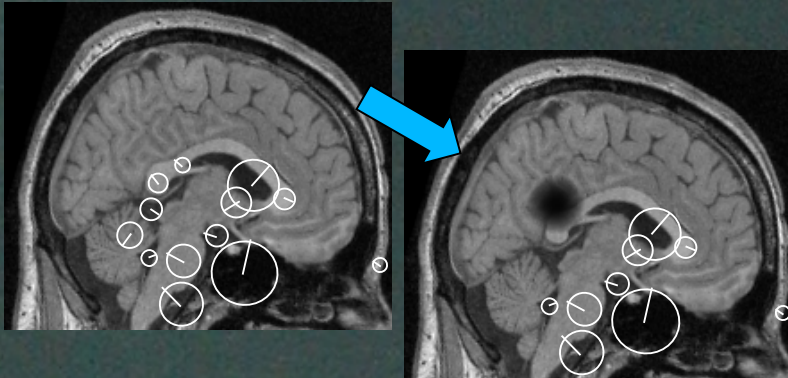
Fitting Error Per Testing Image



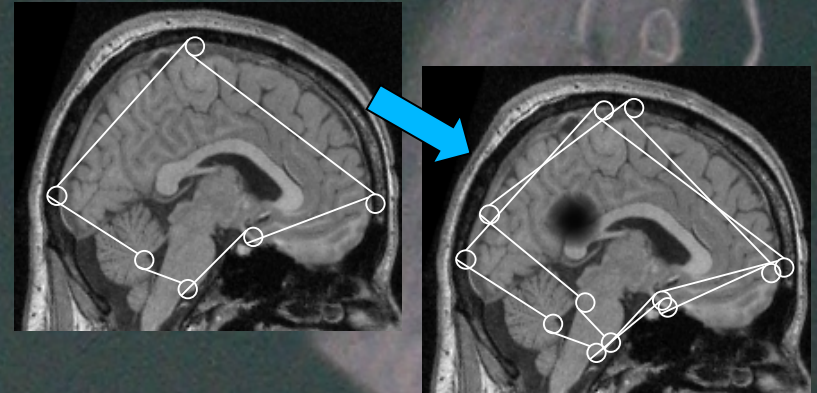
Fitting Stability

- Comparison to global active appearance model (AAM) of Cootes & Taylor
 - Global AAM is unstable to local unexpected appearance change, local perturbation.
 - Significant implications wrt. brain analysis techniques such as morphometry.

Parts-based Model

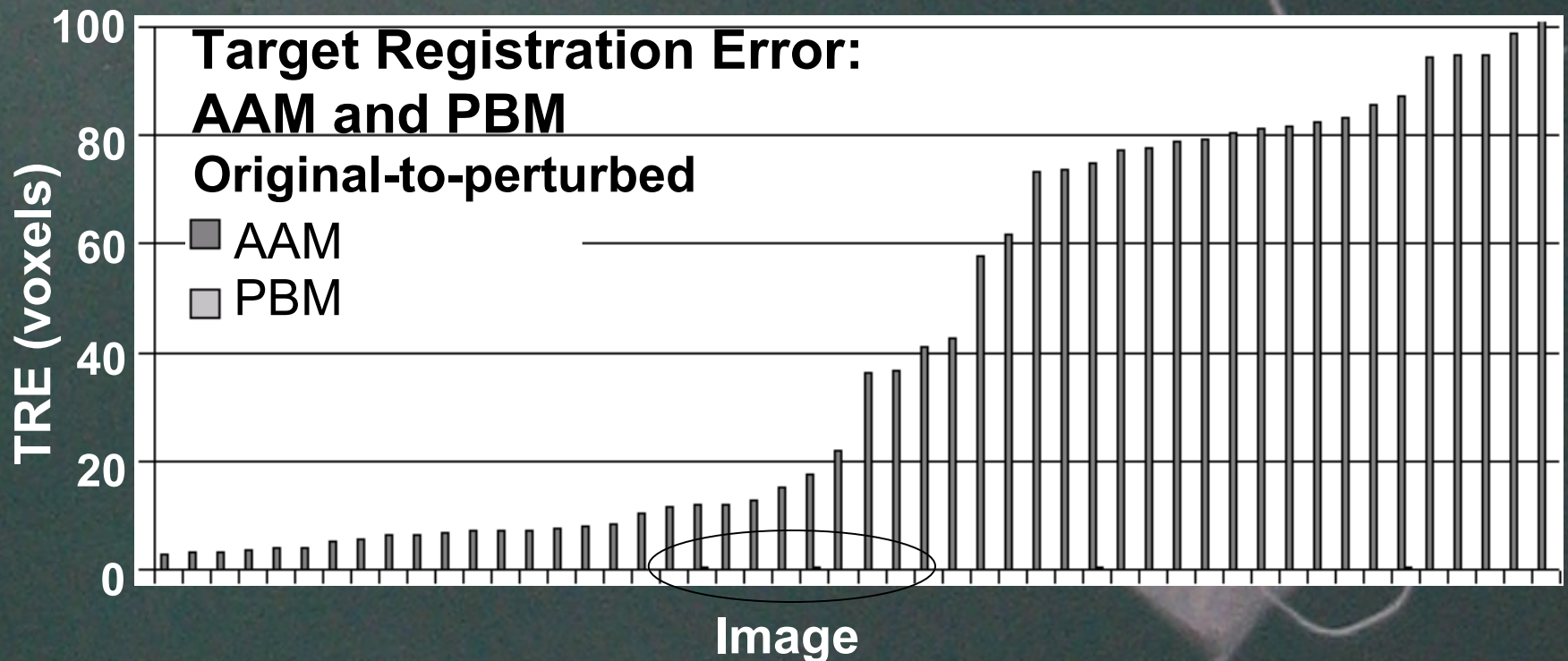


Active Appearance Model



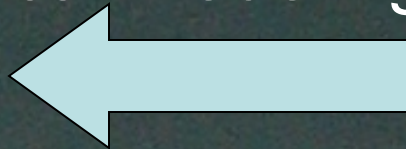
Fitting Stability

- Quantitative comparison
 - Compare fitting before and after perturbation
 - Measure: original-to-perturbed TRE



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Future Challenges

- New scale-invariant features
 - Describe different images characteristics.
 - Features in 1D sound, 3D video or volumetric images.
- Learning
 - Unsupervised learning of 3D object classes?
 - Role of geometry?
- Types of patterns
 - How to describe textures (uncountable patterns)?
 - Repeating structures?

