

6.801/866

# Model-based Vision

T. Darrell

# Endgame

Week	Date	Topic	Requirements	Notes
23	11/26	Model-Based Vision	Req: FP 18	Today
	11/28	Thanksgiving (NO LECTURE)		
24	12/3	Image Databases	Req: FP 25	Guest Lecture: Prof. Stan Sclaroff
25	12/5	Image-Based Rendering	Req: FP 26	Last Lecture; Vision and Graphics... Exam #2 Due
26	12/10	Project Show and Tell		Projects Due Submit 3 Slides

3-5 slides to Louis  
Short narration in-class

- PS3 back today; mean = 82, std.dev. = 13
- Next week we'll distribute extra credit problem(s)

# Model-based Vision

- Hypothesize and test
- Interpretation Trees
- Alignment
- Pose Clustering
- Invariances
- Geometric Hashing
- Medical Imaging Application

# Approach

- Given
  - CAD Models (with features)
  - Detected features in an image
- Hypothesize and test
  - Guess
  - Render
  - Compare

# Recognition by Hypothesize and Test

- General idea
  - Hypothesize object identity and correspondence
  - Recover camera (widely known as backprojection)
  - Render object in camera
  - Compare to image
- Issues
  - where do the hypotheses come from?
  - How do we compare to image (verification)?

# Recognition by Hypothesize and Test

- Simplest approach
  - Construct a correspondence for all object features to every correctly sized subset of image points
    - These are the hypotheses
  - Expensive search, which is also redundant.

# What are the features?

- They have to project like points
  - Lines
  - Conics
  - Other fitted curves
  - Regions (particularly the center of a region, etc.)

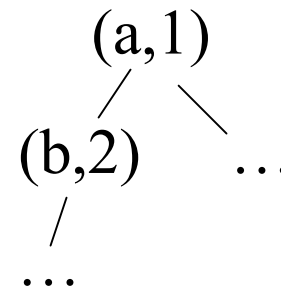
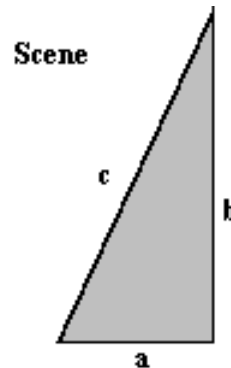
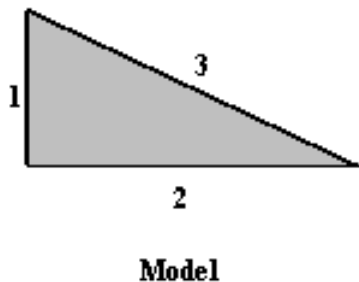
# How to generate hypotheses?

- Brute force
  - L objects with N features
  - M features in image
  - $O(LM^N)$  !
- Add geometric constraints to prune search, leading to *interpretation tree search*
- Try subsets of features (frame groups)...

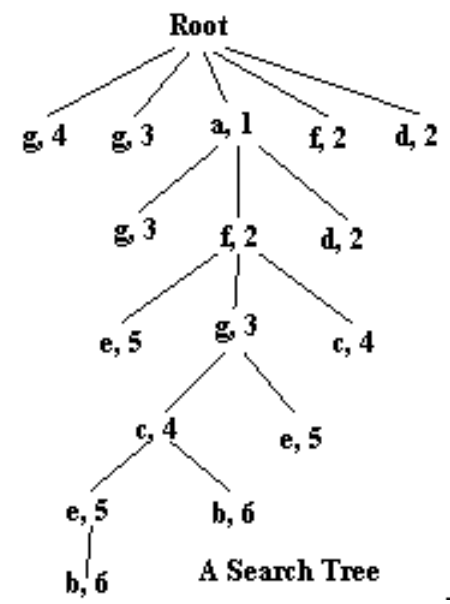
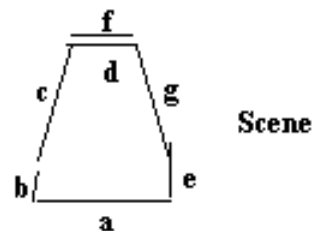
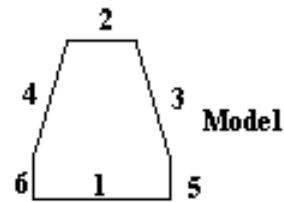
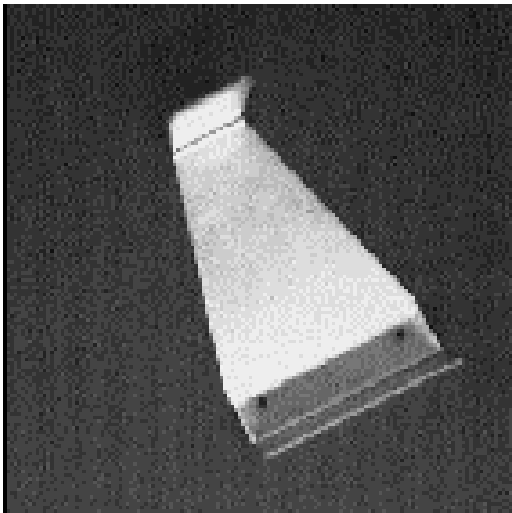


# Interpretation Trees

- Tree of possible model-image feature assignments
- Depth-first search
- Prune when unary (binary, ...) constraint violated
  - length
  - area
  - orientation
- “Wild cards” handle spurious image features



# Interpretation Trees



[ A.M. Wallace. 1988. ]

# Interpretation Trees Demo

- <http://vision.dai.ed.ac.uk/demos/itreal/>

# Configuration Search

- Alignment
  - *Model-based RANSAC*
- Pose clustering
  - *Model-based Hough*

These methods search over pose...

another approach computes a measure *invariant* to configuration change.

# Pose consistency / Alignment

- Correspondences between image features and model features are not independent.
- A small number of correspondences yields a camera --- the others must be consistent with this.

# Pose consistency / Alignment

- Strategy:
  - Generate hypotheses using small numbers of correspondences (e.g. triples of points for a calibrated perspective camera, etc., etc.)
  - Backproject and verify
- Notice that the main issue here is camera calibration
- Appropriate groups are “frame groups”

# Pose consistency / Alignment

- Given known camera type in some unknown configuration (pose)
- Hypothesize configuration from set of initial features
- Frame group -- set of sufficient correspondences to estimate configuration, e.g.,
  - 3 points
  - 3 directions from 1 point
- Backproject
- Test

# Alignment

For all object frame groups  $O$

  For all image frame groups  $F$

    For all correspondences  $C$  between  
      elements of  $F$  and elements  
      of  $O$

      Use  $F$ ,  $C$  and  $O$  to infer the missing parameters  
      in a camera model

      Use the camera model estimate to render the object

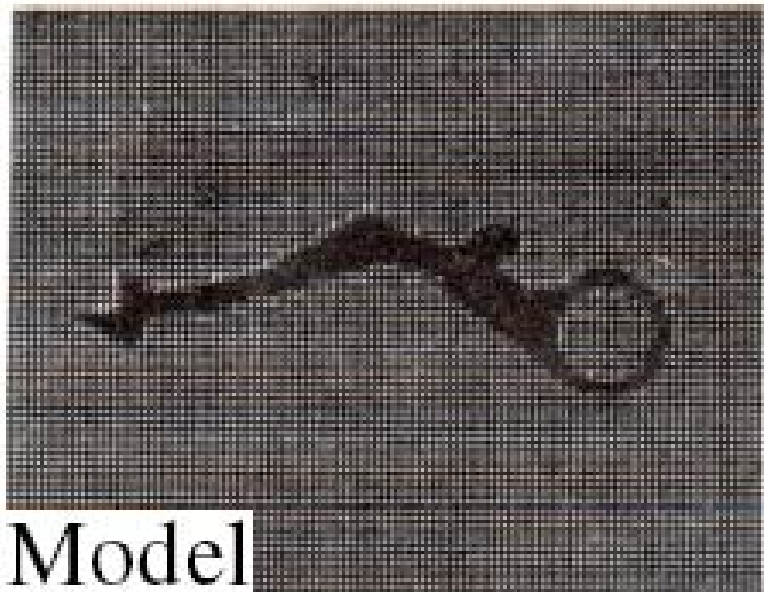
      If the rendering conforms to the image,  
      the object is present

    end

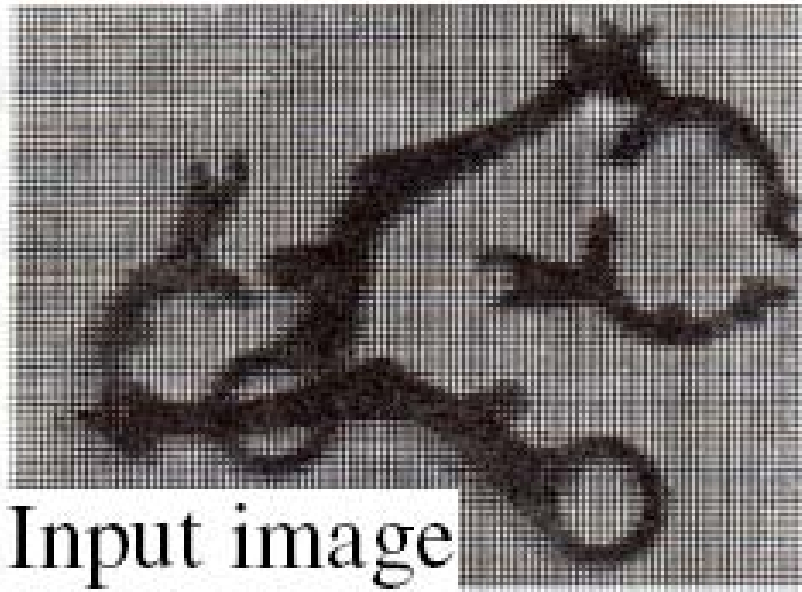
  end

end

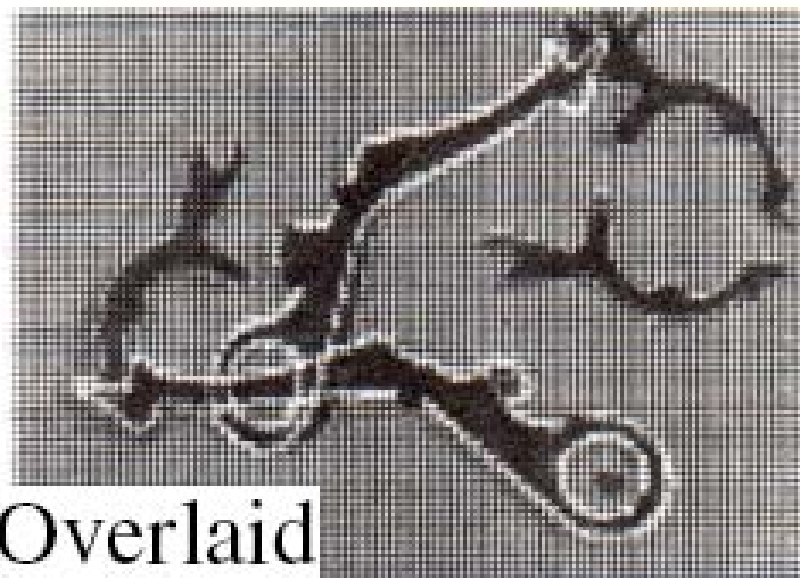




Model



Input image



Overlaid

# Pose clustering

- Voting on Pose
- Each model leads to many correct sets of correspondences, each of which has the same pose
  - Vote on pose, in an accumulator array
  - This is a Hough transform, with all its issues.

# Pose Clustering

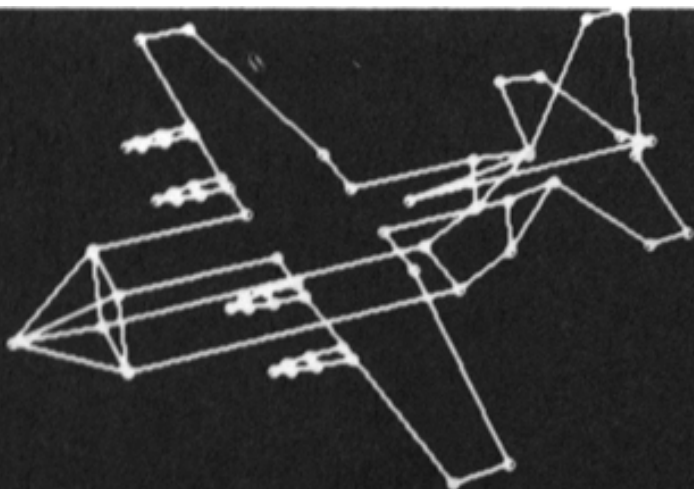
```
For all objects  $O$ 
  For all object frame groups  $F(O)$ 
    For all image frame groups  $F(I)$ 
      For all correspondences  $C$  between
        elements of  $F(I)$  and elements
        of  $F(O)$ 

        Use  $F(I)$ ,  $F(O)$  and  $C$  to infer object pose  $P(O)$ 

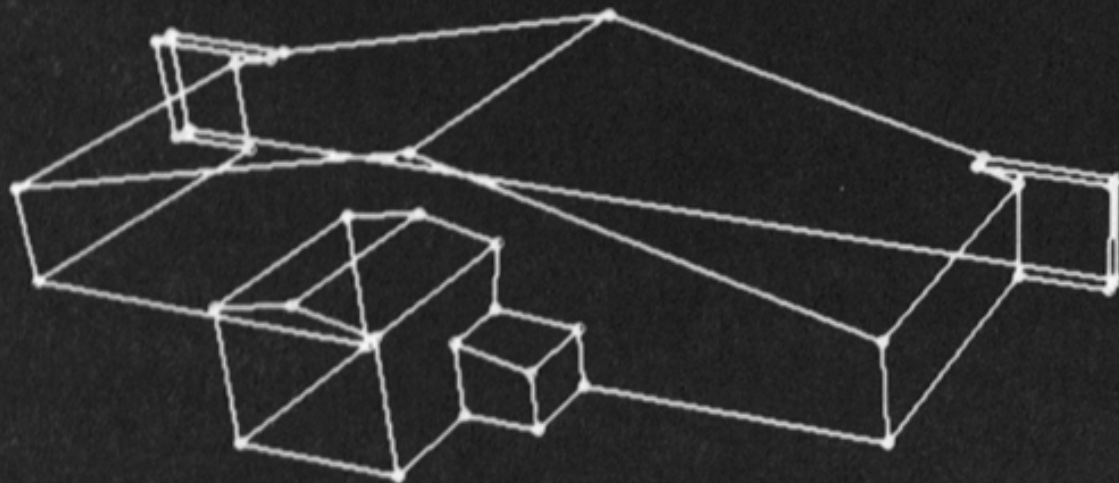
        Add a vote to  $O$ 's pose space at the bucket
        corresponding to  $P(O)$ .
      end
    end
  end
end
For all objects  $O$ 
  For all elements  $P(O)$  of  $O$ 's pose space that have
    enough votes

    Use the  $P(O)$  and the
    camera model estimate to render the object

    If the rendering conforms to the image,
    the object is present
  end
end
```



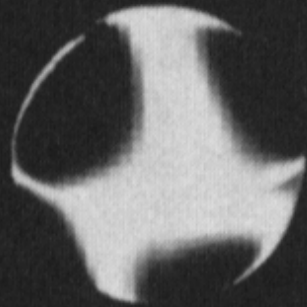
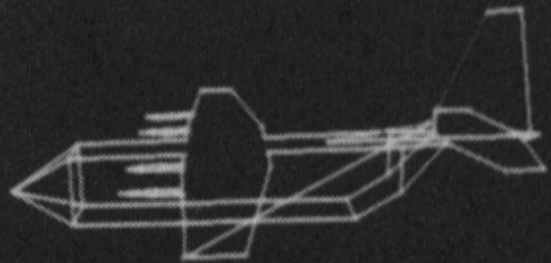
Geo-Calc OBJECT C-130.model



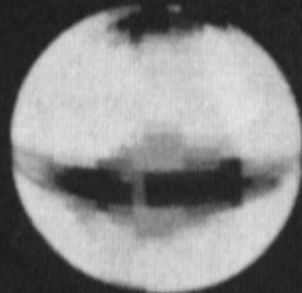
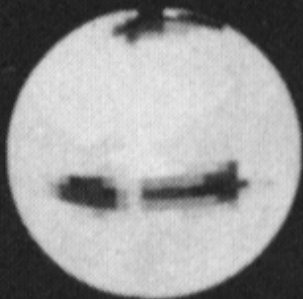
Geo-Calc OBJECT Nosadock.model

# Confidence weighting in Pose clustering

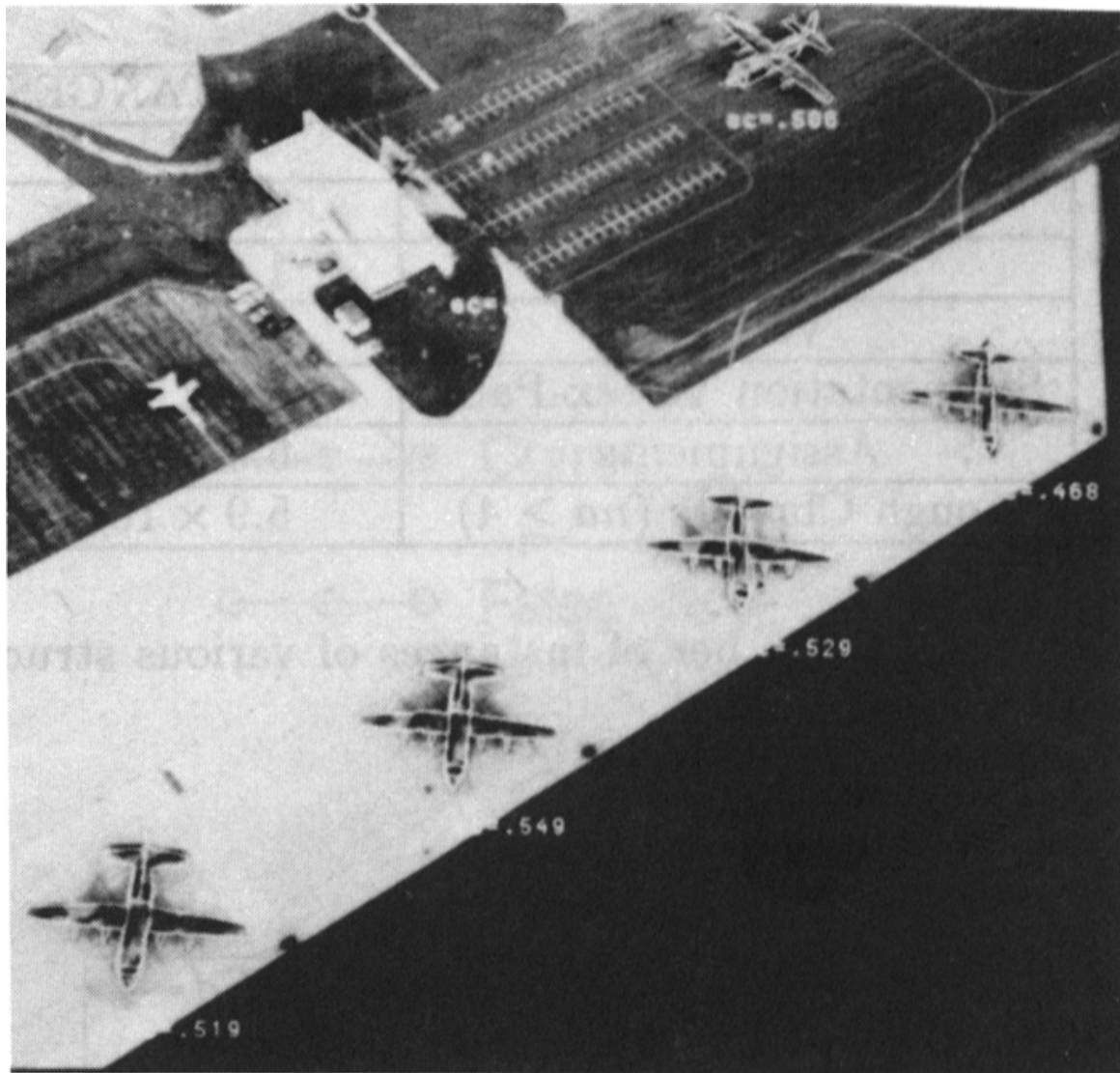
- See where model frame group is reliable (visible!)
- Down-weight / discount votes from frame groups at poses where that frame group is unreliable...



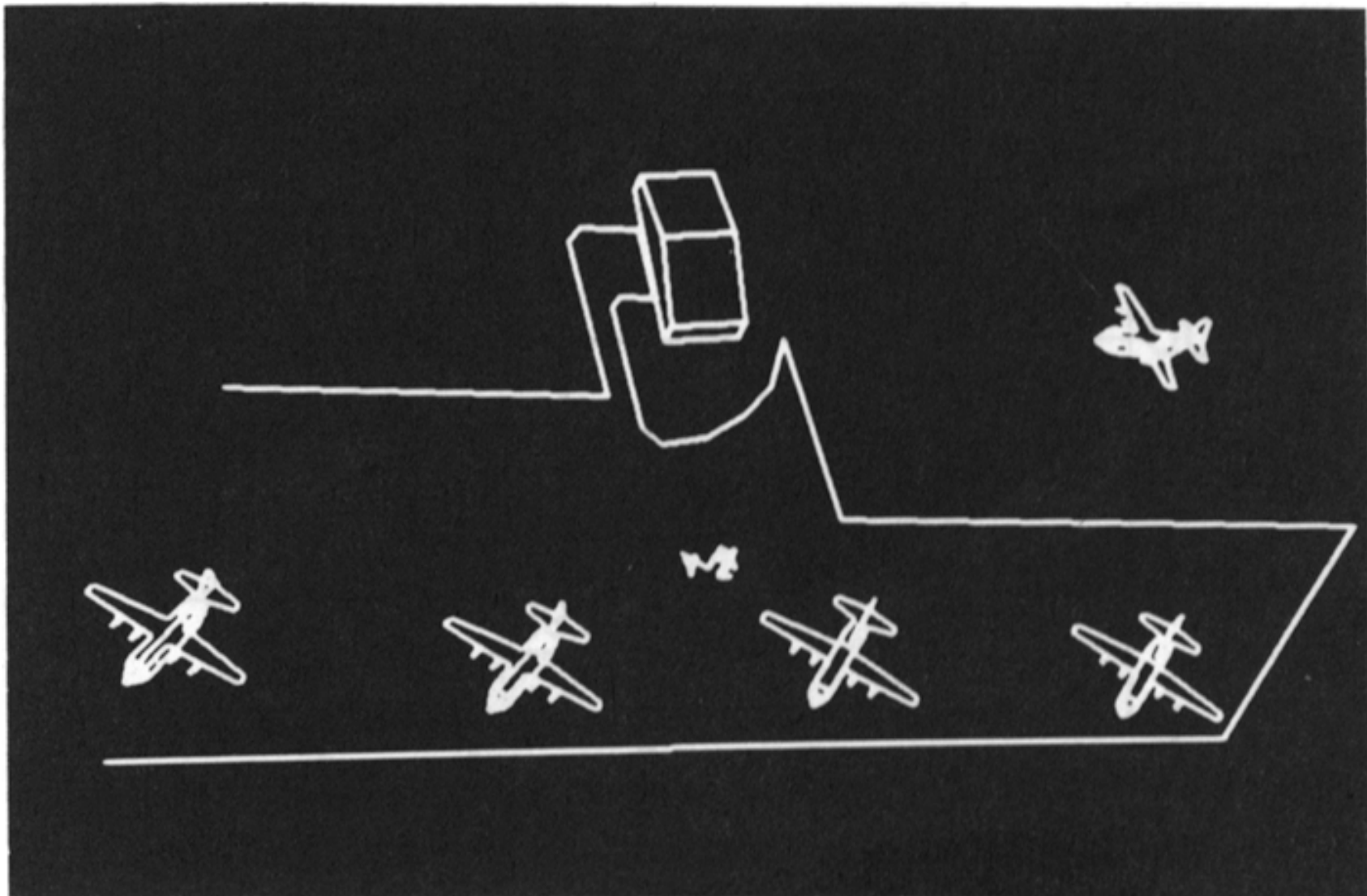
Calc 09.807











# Invariant recognition

- Affine invariants
  - Linear combinations of models
  - Geometric hashing
- Projective invariants
  - Determinant ratio
- Curve invariants

# Invariance

- There are geometric properties that are invariant to camera transformations
- Easiest case: view a plane object in scaled orthography.
- Assume we have three base points  $P_i$  on the object
  - then any other point on the object can be written as

$$P_k = P_1 + \mu_{ka} (P_2 - P_1) + \mu_{kb} (P_3 - P_1)$$

# Invariance

- Now image points are obtained by multiplying by a plane affine transformation, so

$$\begin{aligned} p_k &= AP_k \\ &= A\left(P_1 + \mu_{ka}(P_2 - P_1) + \mu_{kb}(P_3 - P_1)\right) \\ &= p_1 + \mu_{ka}(p_2 - p_1) + \mu_{kb}(p_3 - p_1) \end{aligned}$$

# Invariance

$$P_k = P_1 + \mu_{ka}(P_2 - P_1) + \mu_{kb}(P_3 - P_1)$$

$$\begin{aligned} p_k &= AP_k \\ &= A(P_1 + \mu_{ka}(P_2 - P_1) + \mu_{kb}(P_3 - P_1)) \\ &= p_1 + \mu_{ka}(p_2 - p_1) + \mu_{kb}(p_3 - p_1) \end{aligned}$$

- This means that, if I know the base points in the image, I can read off the  $\mu$  values for the object
  - they're the same in object and in image --- **invariant**
- Suggests a strategy rather like the Hough transform
  - search correspondences, form  $\mu$ 's and vote

# Geometric hashing

- Vote on identity and correspondence using invariants
  - Take hypotheses with large enough votes
- Fill up a table, indexed by  $\mu$ 's, with
  - the base points and fourth point that yield those  $\mu$ 's
  - the object identity

**Algorithm 18.3:** Geometric hashing: voting on identity and point labels

```
For all groups of three image points  $T(I)$ 
  For every other image point  $p$ 
    Compute the  $\mu$ 's from  $p$  and  $T(I)$ 
    Obtain the table entry at these values
      if there is one, it will label the three points in  $T(I)$ 
      with the name of the object
      and the names of these particular points.
    Cluster these labels;
      if there are enough labels, backproject and verify
    end
  end
end
```

# Indexing with invariants

- Voting in geometric hashing is superfluous - we could just go ahead and verify if we get a hit.
- It would be nice to have invariants for perspective cameras
- Groups of features with identity information invariant to pose – *invariant bearing groups*
- Easy for perspective views of plane objects --- we write object points in homogenous coordinates, then the object coordinates are multiplied by a 3x3 matrix with non-zero det.

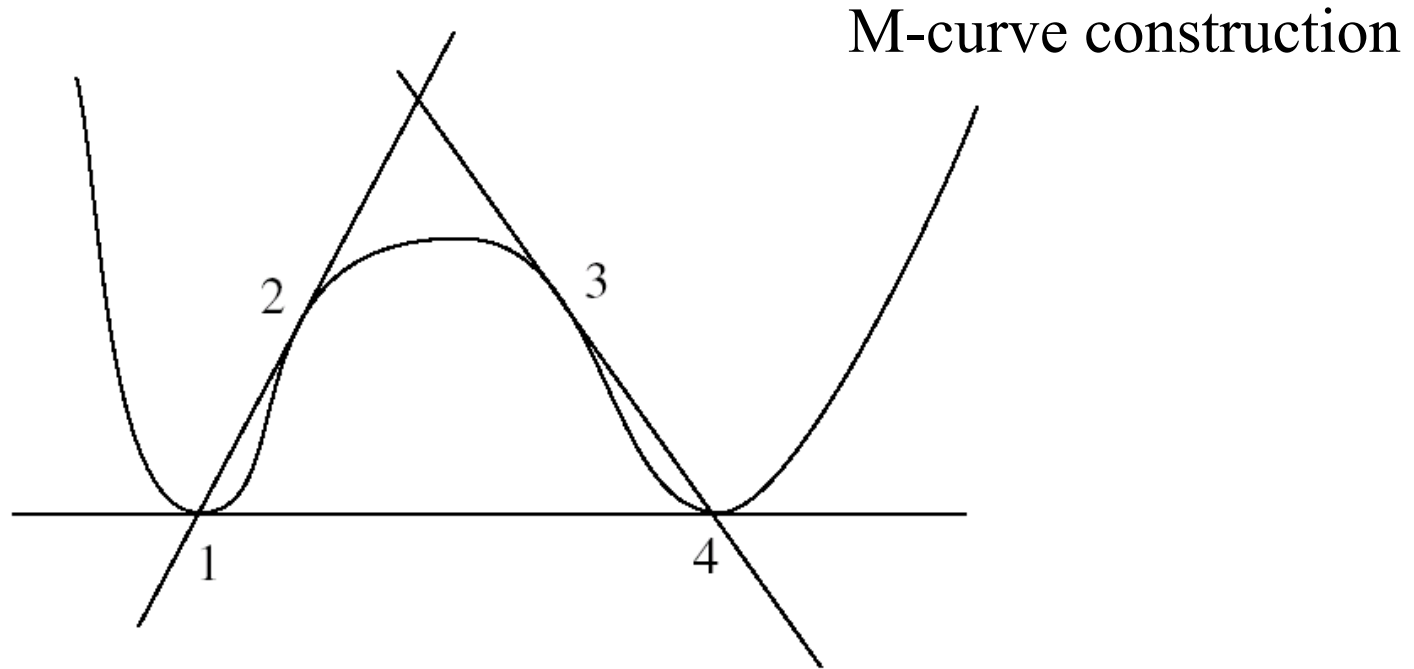


$$\begin{aligned}
\frac{\det([p_i p_j p_k]) \det([p_i p_l p_m])}{\det([p_i p_j p_l]) \det([p_i p_k p_m])} &= \frac{\det([MP_i MP_j MP_k]) \det([MP_i MP_l MP_m])}{\det([MP_i MP_j MP_l]) \det([P_i MP_k MP_m])} \\
&= \frac{\det(M [P_i P_j P_k]) \det(M [P_i P_l P_m])}{\det(M [P_i P_j P_l]) \det(M [P_i P_k P_m])} \\
&= \frac{(\det(M)^2) \det([P_i P_j P_k]) \det([P_i P_l P_m])}{(\det(M)^2) \det([P_i P_j P_l]) \det([P_i P_k P_m])} \\
&= \frac{\det([P_i P_j P_k]) \det([P_i P_l P_m])}{\det([P_i P_j P_l]) \det([P_i P_k P_m])}
\end{aligned}$$

Five points under projective transformations; the text gives several other constructions

# Tangent invariance

- Incidence is preserved despite transformation



- Transform four points above to unit square: measurements in this canonical frame will be invariant to pose.

```
For each type  $T$  of invariant-bearing group
  For each image group  $G$  of type  $T$ 

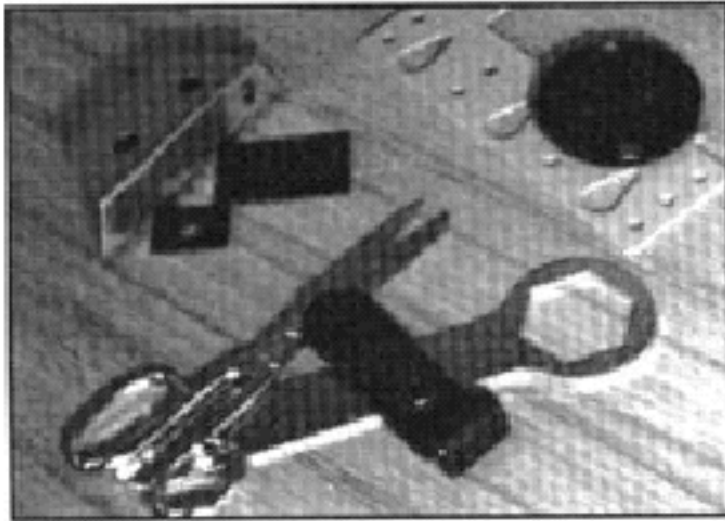
    Determine the values  $V$  of the invariants of  $G$ 

      For each model feature group  $M$  of type  $T$  whose invariants
      have the values  $V$ 

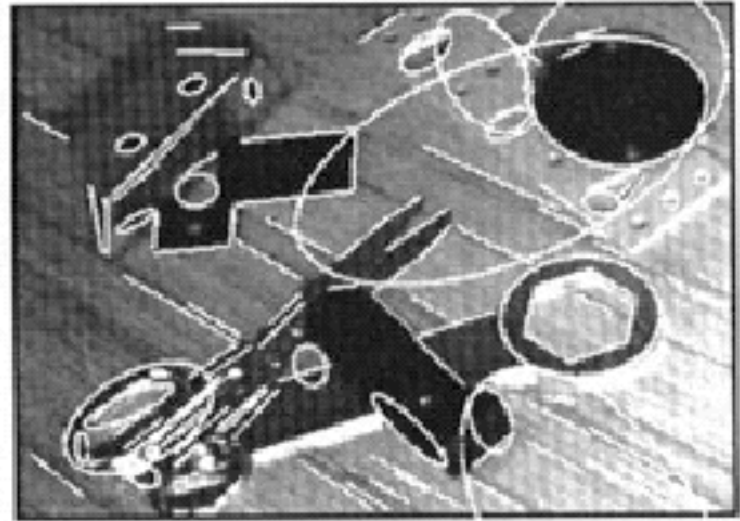
        Determine the transformation that takes  $M$  to  $G$ 

        Render the model using this transformation

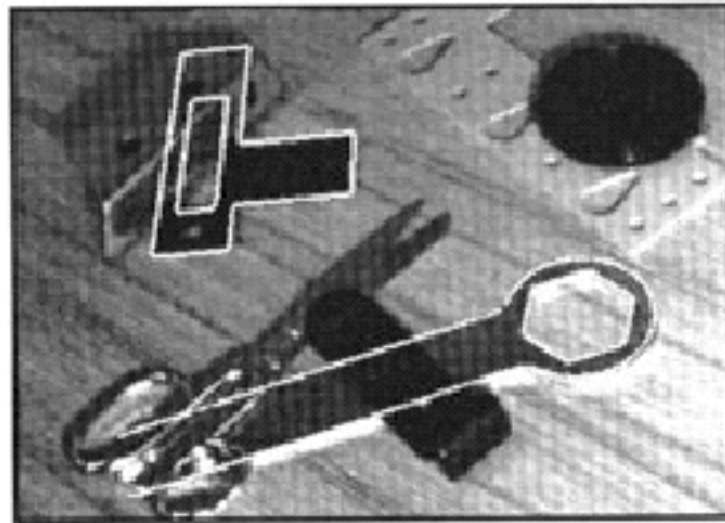
        Compare the result with the image, and accept if
        similar
      end
    end
  end
end
```



**a**

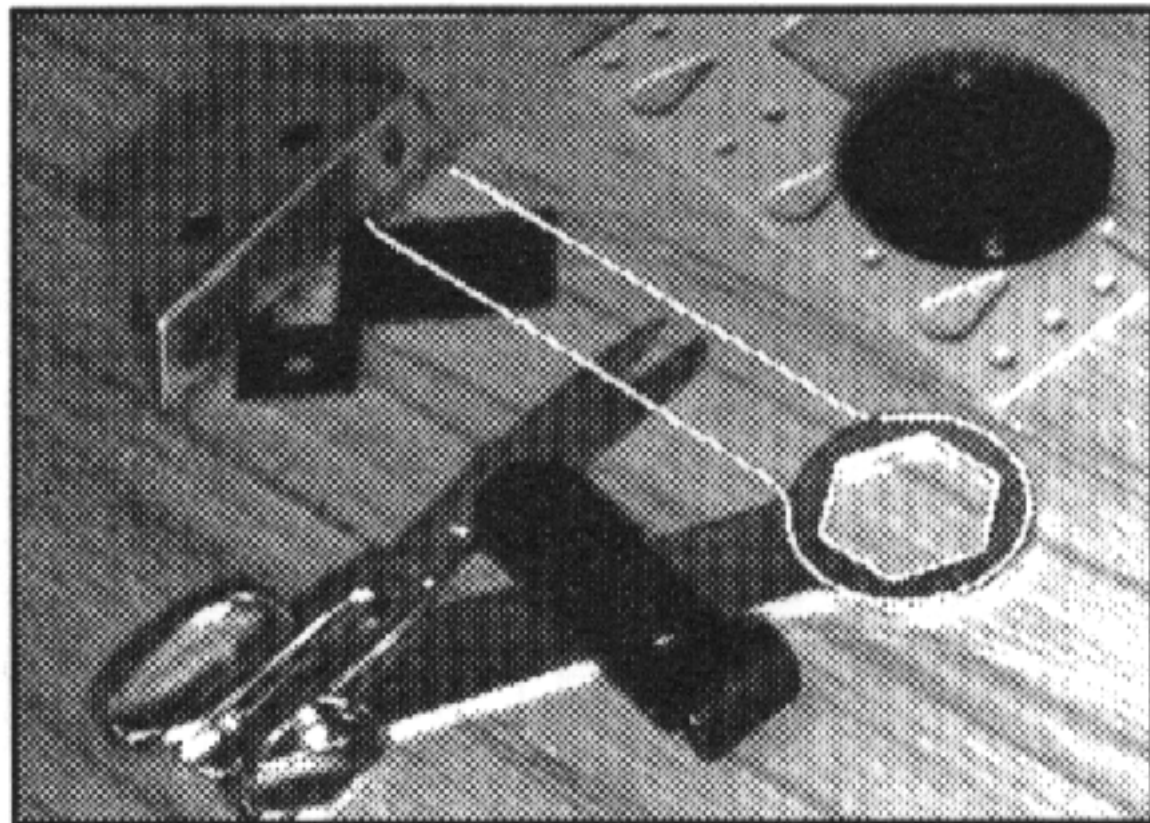


**b**



# Verification

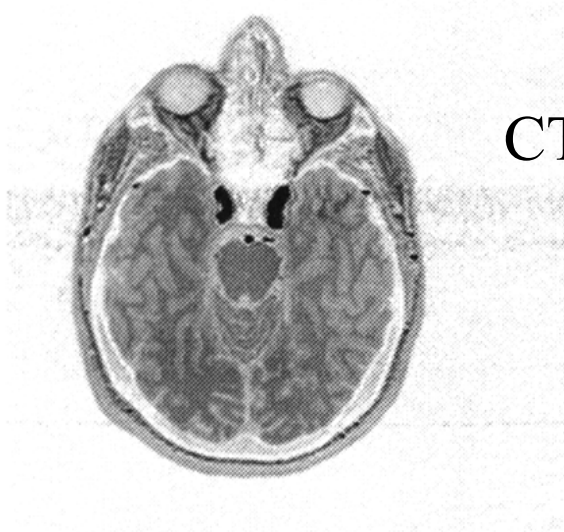
- Edge score
  - are there image edges near predicted object edges?
  - very unreliable; in texture, answer is usually yes
- Oriented edge score
  - are there image edges near predicted object edges with the right orientation?
  - better, but still hard to do well (see next slide)
- No-one's used texture
  - e.g. does the spanner have the same texture as the wood?
- model selection problem
  - more on these later; no-ones seen verification this way, though



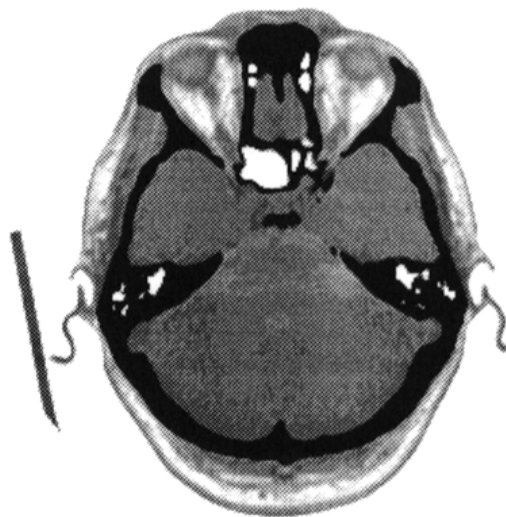
# Application: Surgery

- To minimize damage by operation planning
- To reduce number of operations by planning surgery
- To remove only affected tissue
- Problem
  - ensure that the model with the operations planned on it and the information about the affected tissue lines up with the patient
  - display model information supervised on view of patient
  - **Big Issue:** coordinate alignment, as above

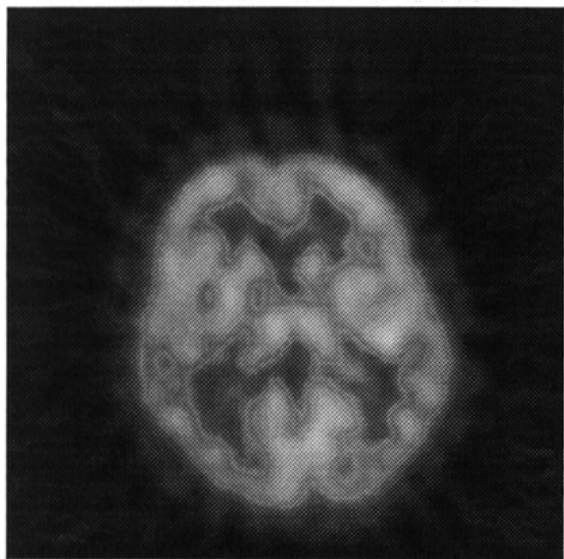
MRI



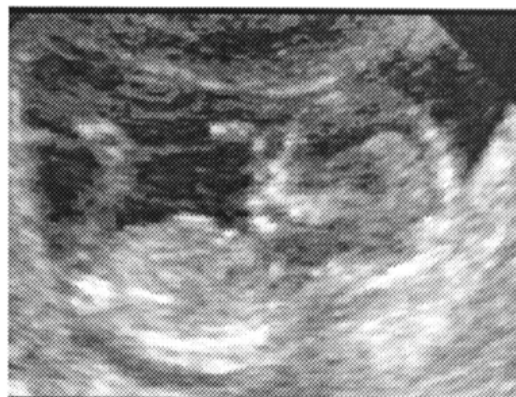
CTI



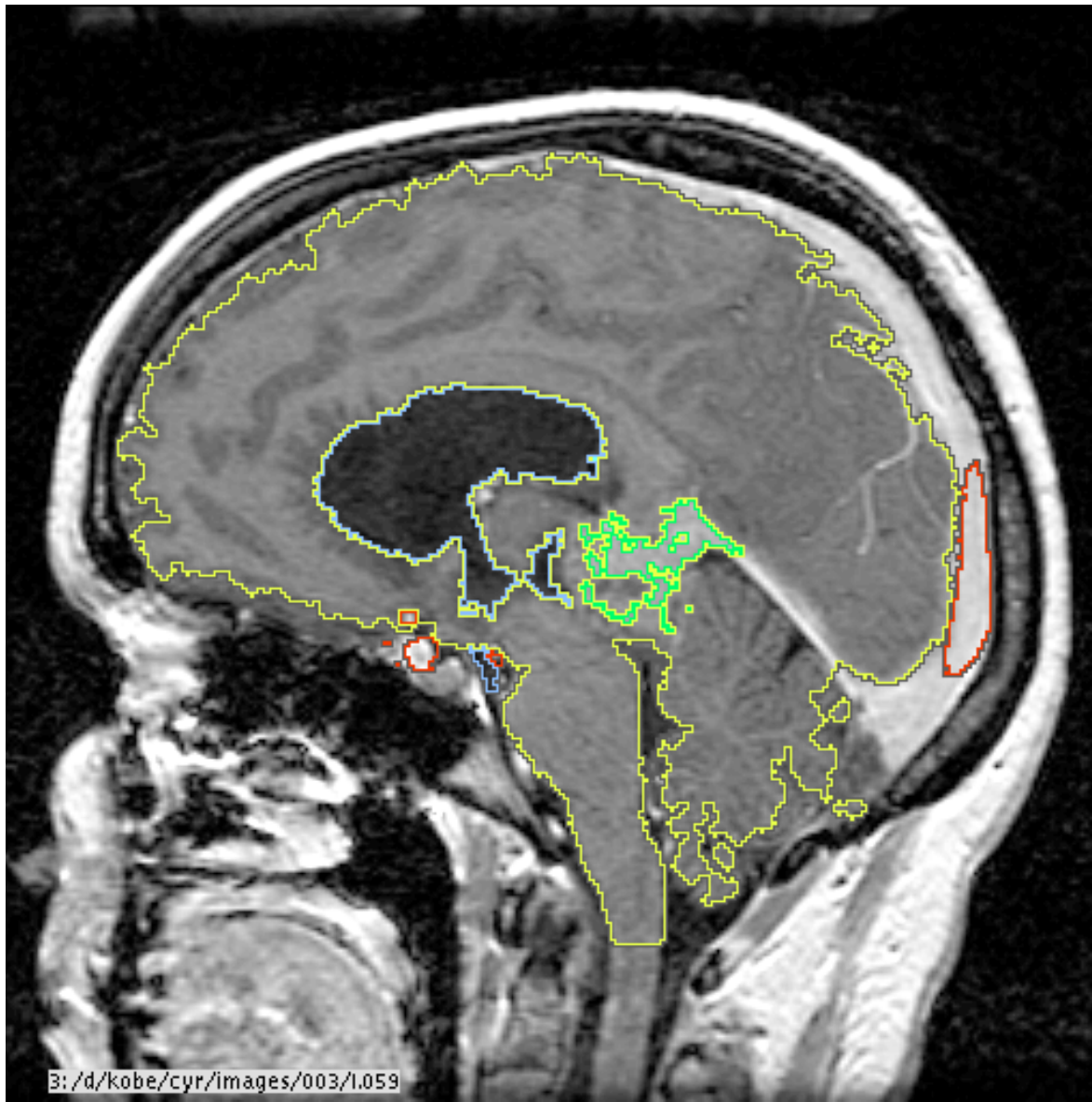
NMI



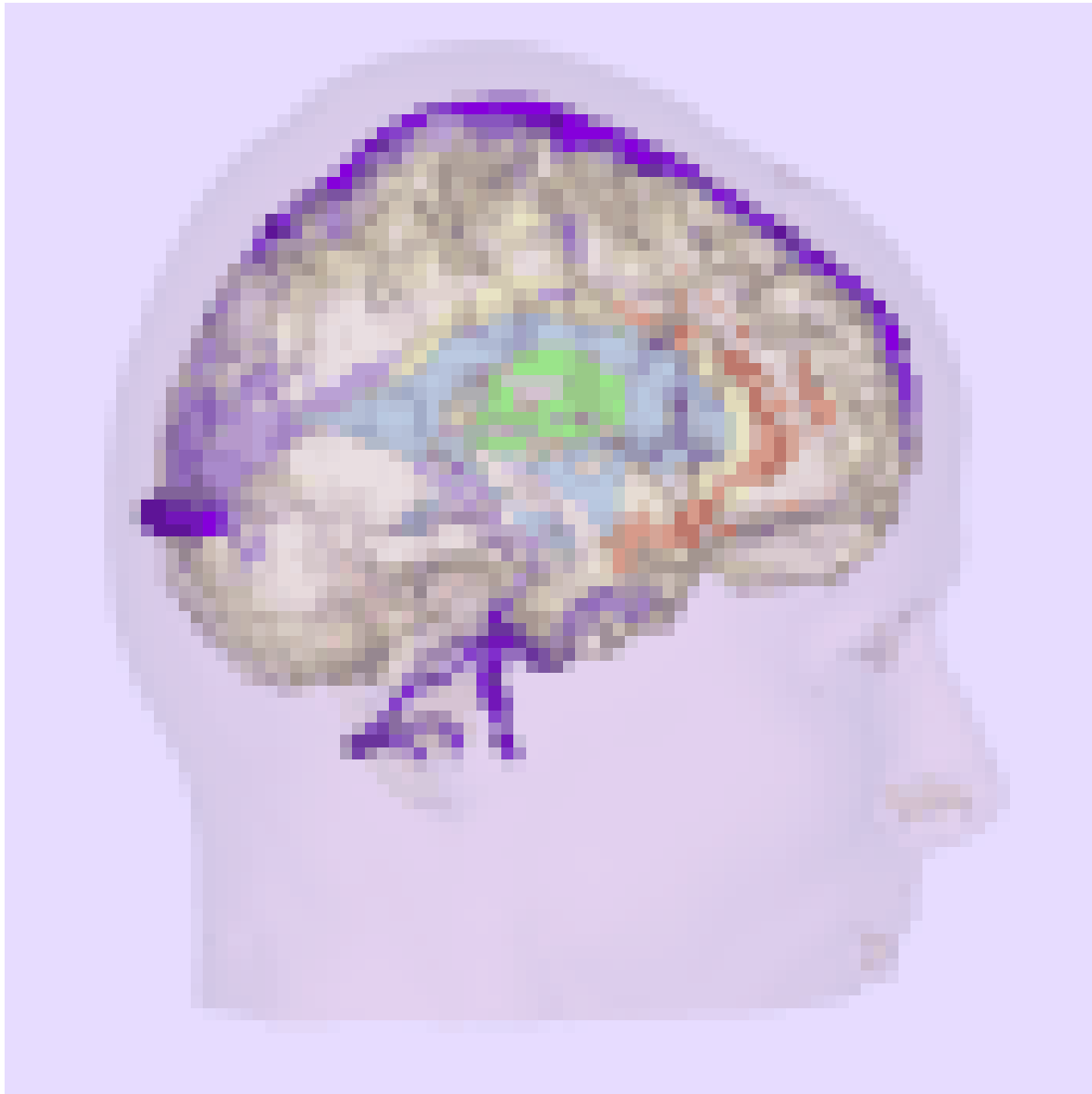
USI



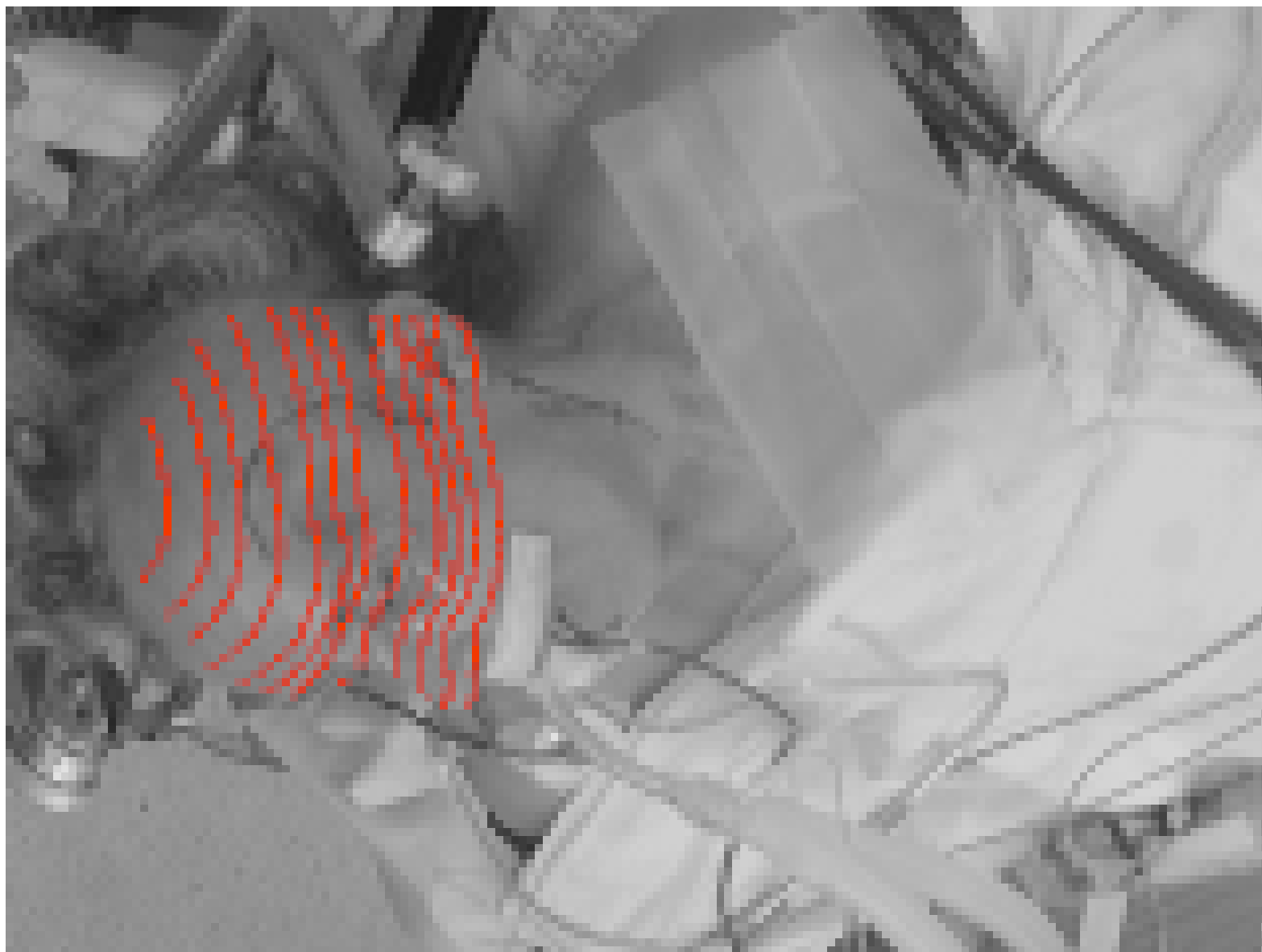




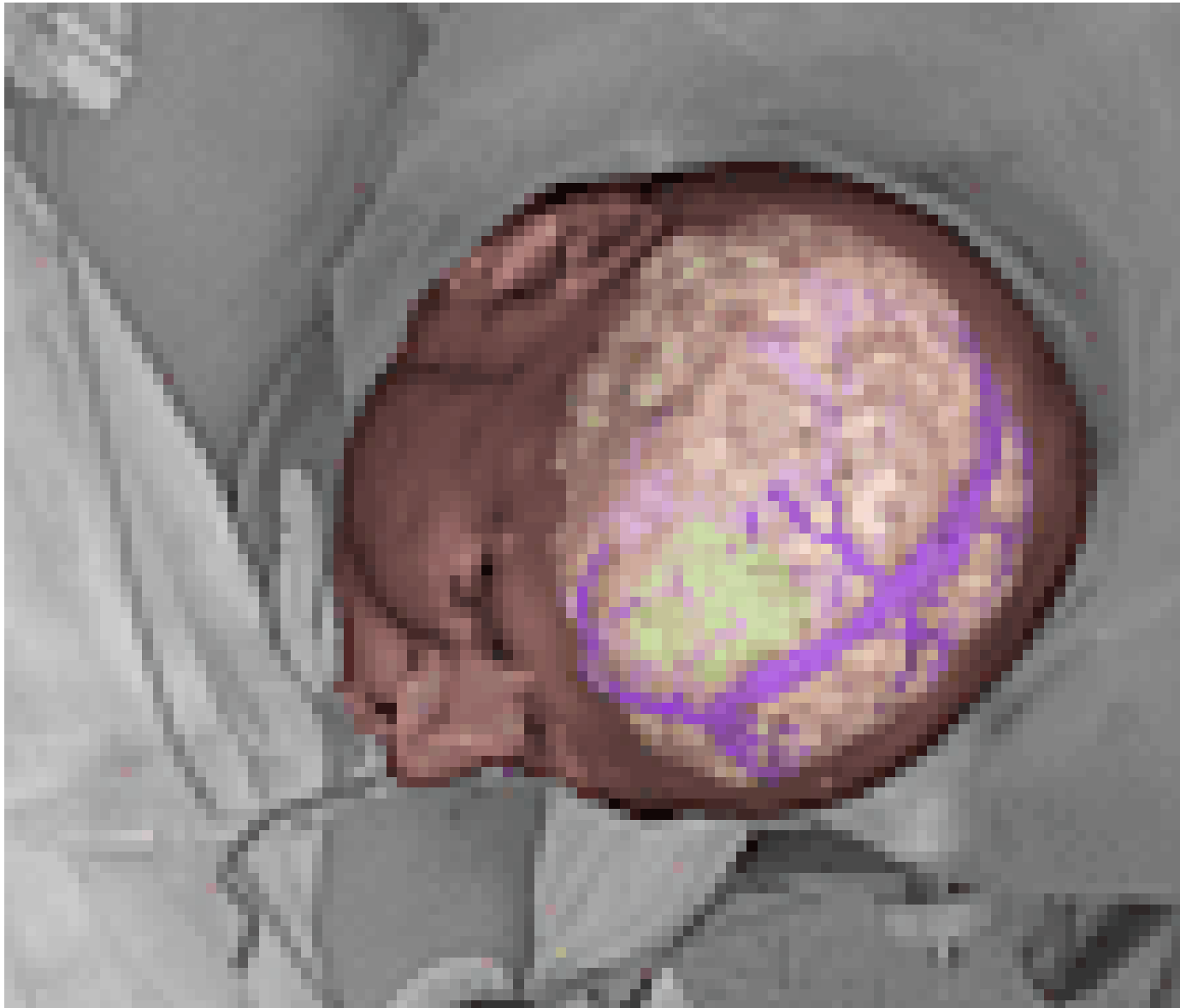
[ Eric Grimson; <http://www.ai.mit.edu/people/welg/welg.html>]



[ Eric Grimson; <http://www.ai.mit.edu/people/welg/welg.html>]



[ Eric Grimson; <http://www.ai.mit.edu/people/welg/welg.html>]



[ Eric Grimson; <http://www.ai.mit.edu/people/welg/welg.html>]



[ Eric Grimson; <http://www.ai.mit.edu/people/welg/welg.html>]

# Model-based Vision

- Hypothesize and test
- Interpretation Trees
- Alignment
- Pose Clustering
- Invariances
- Geometric Hashing
- Medical Imaging Application

[Figures from Forsythe & Ponce unless otherwise attributed]