

Computer Vision

18AI742

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Registration

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Registration

Contents

- 1) Registering rigid objects
- 2) Model-based vision: registering rigid objects with projection
- 3) Registering deformable objects
- 4) Conclusion
- 5) Q&A

$$\nabla \cdot \mathbf{E} = \rho / \epsilon_0$$

$$\nabla \cdot \mathbf{B} = 0$$

$$\nabla \times \mathbf{E} = - \frac{\partial \mathbf{B}}{\partial t}$$

$$\nabla \times \mathbf{B} = \mu_0 \epsilon_0 \frac{\partial \mathbf{E}}{\partial t} + \mu_0 \mathbf{j}_c$$

where

$$\nabla = \hat{\mathbf{i}} \frac{\partial}{\partial x} + \hat{\mathbf{j}} \frac{\partial}{\partial y} + \hat{\mathbf{k}} \frac{\partial}{\partial z}$$

Registration

Registration - finding a transformation that takes one dataset to another

transformation is rotation, translation, and perhaps scale

pose—the position and orientation in world coordinates

MRI image (which is a 3D dataset) of a patient's interior

to superimpose on a view of the real patient to help guide a surgeon

Pose consistency

different groups of features on rigid object will all report the same pose for the object

2D image template of building that we want to find in an overhead aerial image

use a match quality score to tell whether we have found the right building

solve these problems using search, exploiting a property

any search to register rigid objects should be simple

Registration under projection with camera consistency

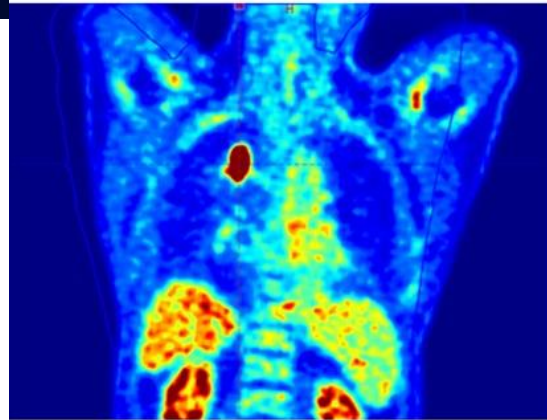
image of a 3D object, needs to register the object to the image

same search algorithms that register datasets of the same dimension?

Camera consistency - all the features in the image are viewed in the same camera

need to find only a small set of features to estimate the pose of rigid object

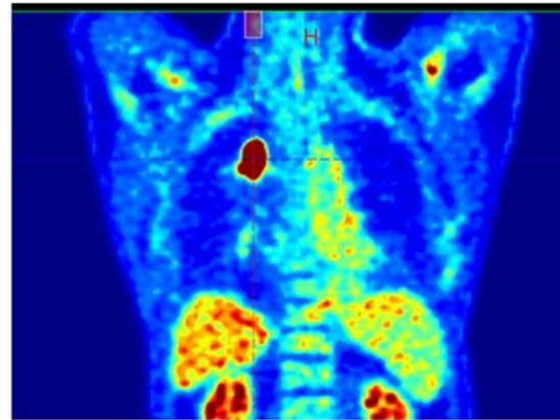
Registration



Original FDG PET



**Image
Registration**



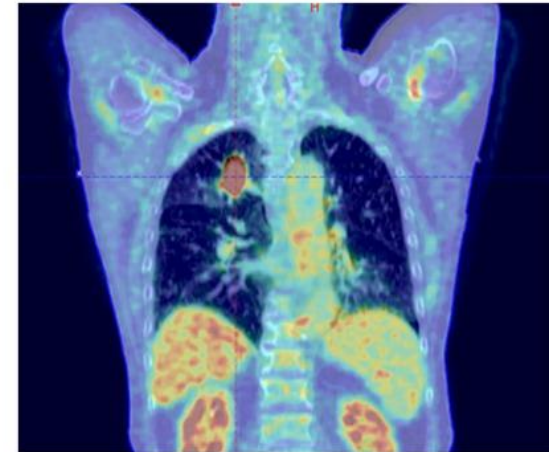
Registered FDG PET



Original CT

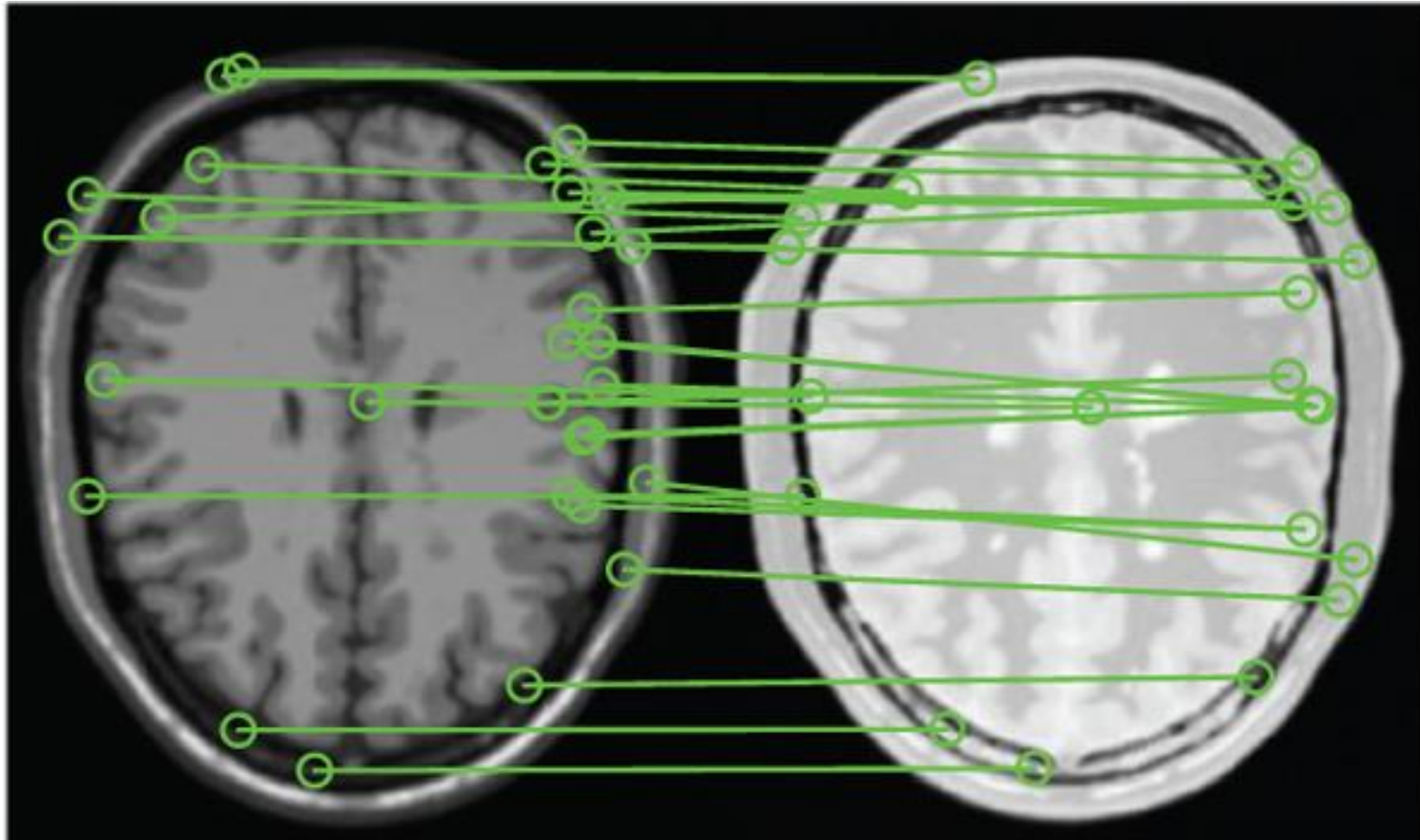


**Image
Fusion**



Fused
CT-PET Image

Registration



Registering rigid objects

two point sets, $S = \{x_i\}$ a source set and $T = \{y_j\}$, a target set

Target set is a rotated, translated, and scaled version of the source set

$c(i)$ for the index of point in the target set corresponding to the i th source point.

$$\sum_i \left[(s\mathcal{R}(\theta)x_i + t) - y_{c(i)} \right]^2$$

$$\mathcal{G}(s, \theta, t)\mathcal{S} = \{ (s\mathcal{R}(\theta)x_i + t) \mid x_i \in \mathcal{S} \}$$

Iterated closest points algorithm

For any $y_j \in T$, there is some $z_i \in G$ that is closest.

Index of the closest such point $c(i, (s, \theta, t))$.

Estimate of the transformation $(s, \theta, t)(n)$.

iterating: (a) transforming $p \in S$; (b) for p , finding closest point in T

(c) re-estimating the transformation with least squares.

Searching for Transformations via Correspondences

Iterated closest points algo might encounter numerous local minima

Alternative is to search the space of correspondences

in the case of rigid objects a relatively small set of correspondences is enough

tokens, rather than points such as line-segments, corners, or even point-like features blobs

frame-bearing groups for estimating transformations from 2D to 2D

Transformation	Frame-bearing groups
Rigid (Euclidean)	One point and one direction, or two points, or one line and one point
Rigid and scale	Two points, or one line and one point off the line
Affine	Three points, not co-linear

frame-bearing groups for estimating transformations from 3D to 3D

Transformation	Frame-bearing groups
Rigid (Euclidean)	Three points, or one line and one point off the line, or two intersecting lines
Rigid and scale	Three points, or one line and one point off the line, or two intersecting lines and a point off their plane.
Affine	Four points, no two co-planar

using RANSAC

- 1 Select a frame-bearing group for the target and for the source at random;
- 2 Compute a correspondence between the source and target elements
- 3 from this compute a transformation
- 4 Apply the transformation to the source dataset
- 5 compute a score comparing the transformed source to the target

Application: Building Image Mosaics

One way to photograph a big, imposing object in detail is

to take numerous small photographs, then patch them together

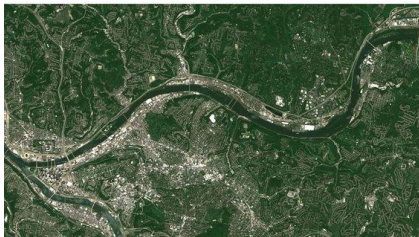
Image mosaics can now be built by registering digital images

image frames taken by an orthographic camera attached to an aircraft

frames from a video taken by an aircraft overflying an airport for mosaicing



Application: Building Image Mosaics



Cylindrical/Spherical panorama

Fixed camera collecting video, By registering frames with one another

we can make estimates of (a) moving objects and (b) background,

Cylindrical/spherical panorama, a set of pixel samples that mimic the image produced by a

Cylindrical/spherical camera

perspective camera were to rotate about its focal point.

Homography

Nothing about camera is known, the map between the relevant portions of I_1 and I_2

plane projective transformation, sometimes known as a homography

Knowing more about the camera and the circumstances might result in

a more tightly constrained transformation

Homography

In homogeneous coordinates, the transformation that takes the point $x_1 = (x_1, y_1, 1)$ in \mathcal{I}_1 to its corresponding point in \mathcal{I}_2 , $x_2 = (x_2, y_2, 1)$, has the form of a generic 3×3 matrix with nonzero determinant. Write \mathcal{H} for this matrix. We can estimate its elements using four corresponding points on the plane. Write $x_1^{(i)} = (x_1^{(i)}, y_1^{(i)}, 1)$ for the i th point in \mathcal{I}_1 , which corresponds to $x_2^{(i)} = (x_2^{(i)}, y_2^{(i)}, 1)$. Now we have

$$\begin{pmatrix} x_2^{(i)} \\ y_2^{(i)} \end{pmatrix} = \begin{pmatrix} \frac{h_{11}x_1^{(i)} + h_{12}y_1^{(i)} + h_{13}}{h_{31}x_1^{(i)} + h_{32}y_1^{(i)} + h_{33}} \\ \frac{h_{21}x_1^{(i)} + h_{22}y_1^{(i)} + h_{23}}{h_{31}x_1^{(i)} + h_{32}y_1^{(i)} + h_{33}} \end{pmatrix},$$

Homography

in the unknown entries of the matrix for each pair of corresponding points, i.e.,

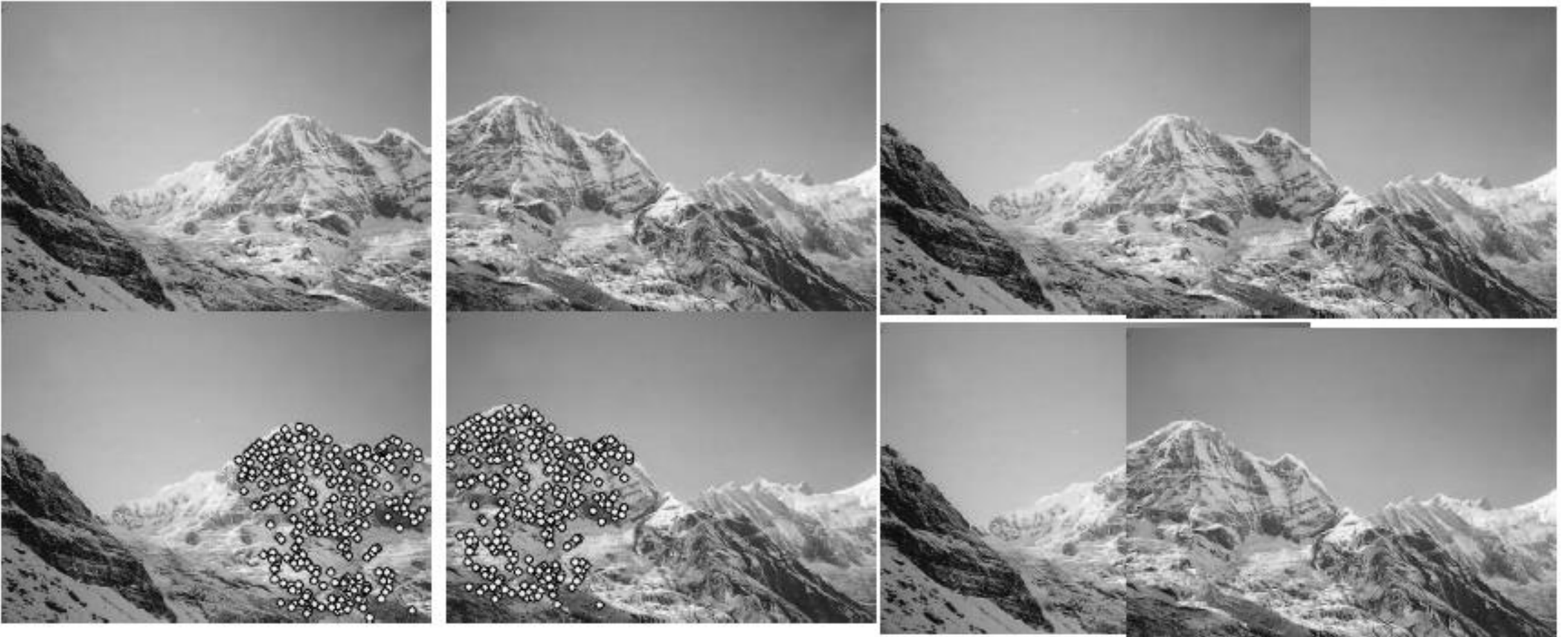
$$\begin{aligned}x_2^{(i)}(h_{31}x_1^{(i)} + h_{32}y_1^{(i)} + h_{33}) - (h_{11}x_1^{(i)} + h_{12}y_1^{(i)} + h_{13}) &= 0 \\y_2^{(i)}(h_{31}x_1^{(i)} + h_{32}y_1^{(i)} + h_{33}) - (h_{21}x_1^{(i)} + h_{22}y_1^{(i)} + h_{23}) &= 0.\end{aligned}$$

when we have a large set of corresponding points. In this case, we should minimize as a function of \mathcal{H}

$$\sum_{i \in \text{points}} g \left(\left(x_2^{(i)} - \frac{h_{11}x_1^{(i)} + h_{12}y_1^{(i)} + h_{13}}{h_{31}x_1^{(i)} + h_{32}y_1^{(i)} + h_{33}} \right)^2 + \left(y_2^{(i)} - \frac{h_{21}x_1^{(i)} + h_{22}y_1^{(i)} + h_{23}}{h_{31}x_1^{(i)} + h_{32}y_1^{(i)} + h_{33}} \right)^2 \right)$$

where g could be the identity function, which is not a good idea if we have outliers, or is an M-estimator. This function is invariant to the scale of \mathcal{H} , so we need

rectified by a translation



rectified with a homography



Error accumulation

1, 2, and 3, register 1 to 2, then 2 to 3

$T_{2 \rightarrow 1}$ for the estimated transformation that takes image two into image one's frame

$T_{2 \rightarrow 1} \circ T_{3 \rightarrow 2}$ might not be a good estimate of $T_{3 \rightarrow 1}$

Resulting in error accumulation

bundle adjustment

estimate all registrations in one go, using all error terms

choose a coordinate frame within which to work frame of the first image

search for a set of maps that take each other image into that frame

minimize the sum of squared errors between all matching pairs of points.

bundle adjustment

of points. For our example, write $(x^{(i)}, x^{(k)})_j$ for the j th tuple consisting of a point $x^{(i)}$ in image i that matches a point $x^{(k)}$ in image k . We would estimate $\mathcal{T}_{2 \rightarrow 1}$ and $\mathcal{T}_{3 \rightarrow 1}$ by minimizing

$$\begin{aligned} & \sum_{j \in 1, 2 \text{ matches}} g(\|x_j^{(1)} - \mathcal{T}_{2 \rightarrow 1} x_j^{(2)}\|^2) + \\ & \sum_{j \in 1, 3 \text{ matches}} g(\|x_j^{(1)} - \mathcal{T}_{3 \rightarrow 1} x_j^{(3)}\|^2) + \\ & \sum_{j \in 2, 3 \text{ matches}} g(\|\mathcal{T}_{2 \rightarrow 1} x_j^{(2)} - \mathcal{T}_{3 \rightarrow 1} x_j^{(3)}\|^2) \end{aligned}$$

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orthographic camera

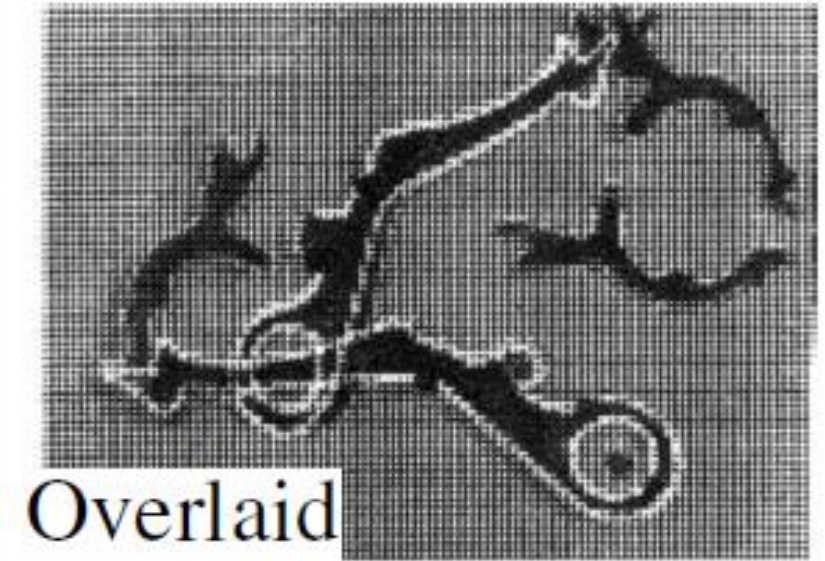
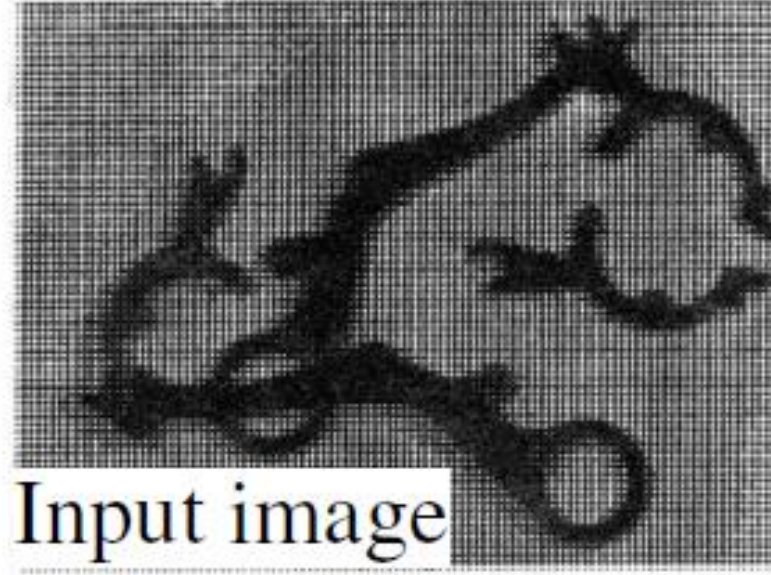
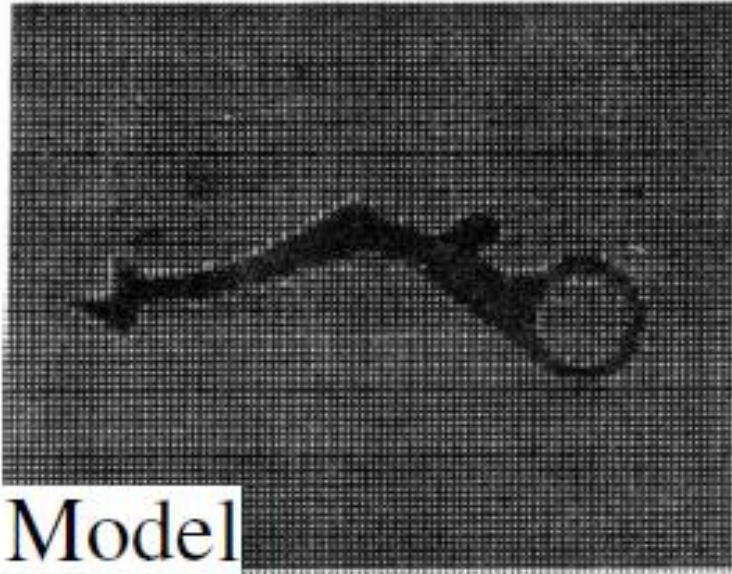
need to calibrate the camera, and on what camera model we impose.

cannot determine depth to the 3D object

correspondences between three points are enough to estimate rotation,

two observable components of translation, and scale

alignment



Comparing Transformed and Rendered Source to Target

render, a general-purpose description for producing an image from models

encompassing everything from constructing line drawings to

producing physically accurate shaded images.

render the transformed object model using our camera model.

Comparing Transformed and Rendered Source to Target

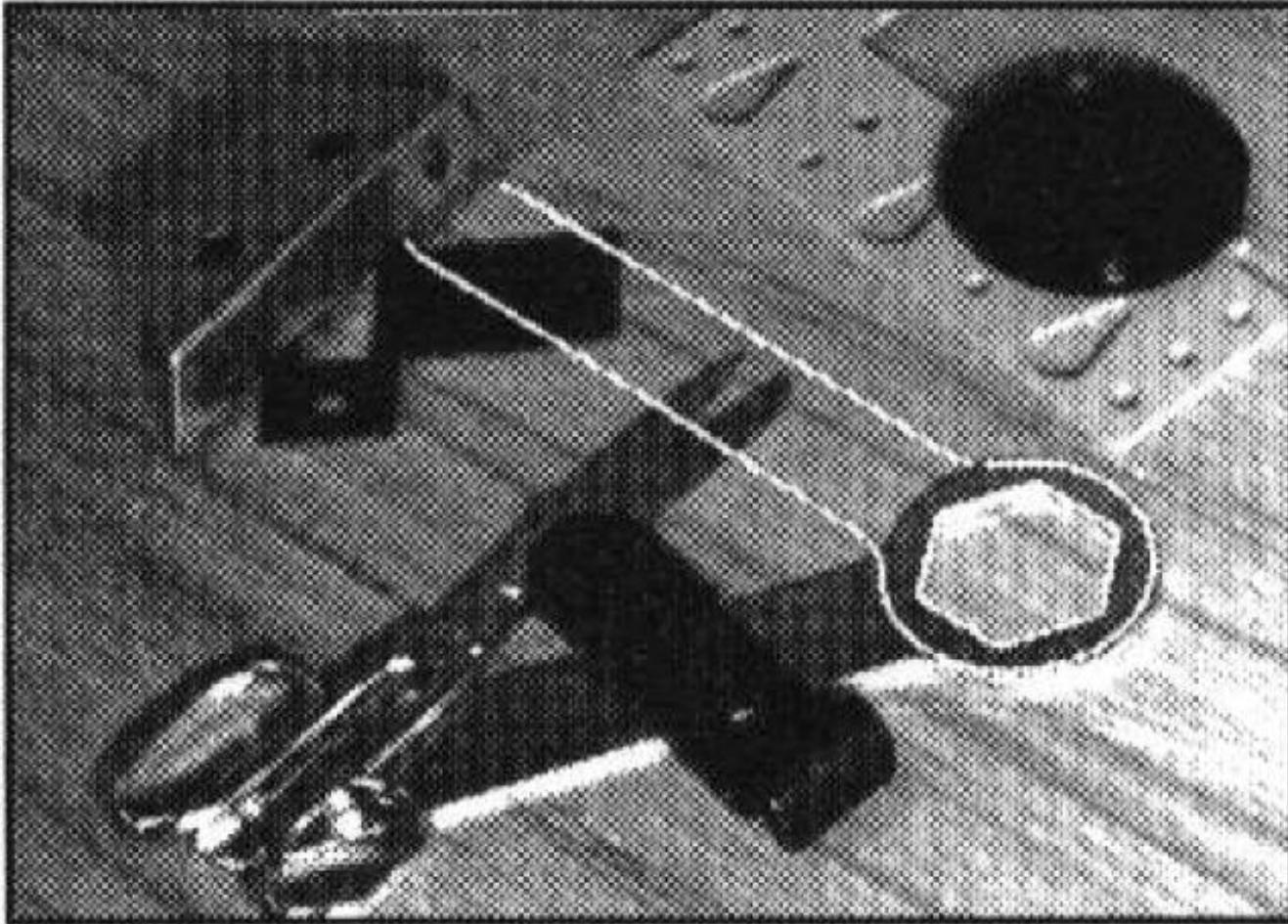
comparisons should be robust to changes in illumination

overlay object silhouette edges on image using camera model, and score

absence of edges lying near these boundaries could well be a quite reliable sign

affects the contrast sensitivity so that the objects disappear

Edge orientation can be a deceptive cue for verification



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Deforming Texture with Active Appearance Models

texture on the face is an important cue driving the match

mesh is placed over an image of a face.

Each point on this triangle has a reference intensity value

obtain by querying the image at that location on the triangle.

Barycentric coordinates

querying the image at that location on the triangle. Write v_1, v_2, v_3 for the vertices of the triangle. We can represent interior points of the triangle using *barycentric coordinates*; with a point in the reference triangle given by (s, t) such that $0 \leq s \leq 1$, $0 \leq t \leq 1$ and $s + t \leq 1$, we associate the point

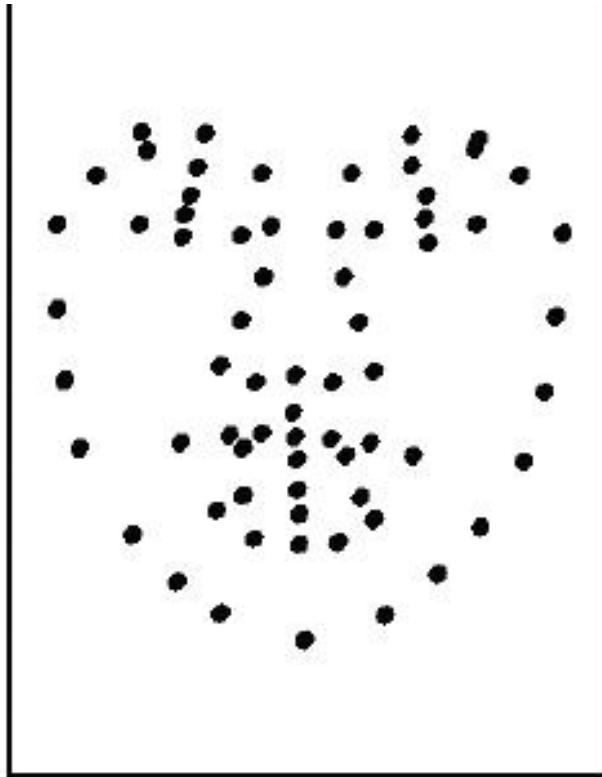
$$p(s, t; v) = sv_1 + tv_2 + (1 - s - t)v_3$$

(which lies inside the triangle). The reference intensity value associated with the point (s, t) for the triangle (v_1, v_2, v_3) is $\mathcal{I}_o(p(s, t; v))$.

reasonable triangulation of the original set of points.



Reference points



Relaxed points



Relaxed intensity

Different face intensity masks generated by moving deformation parameters to different values.



Active appearance models registered to face images



Initial

3 it.s

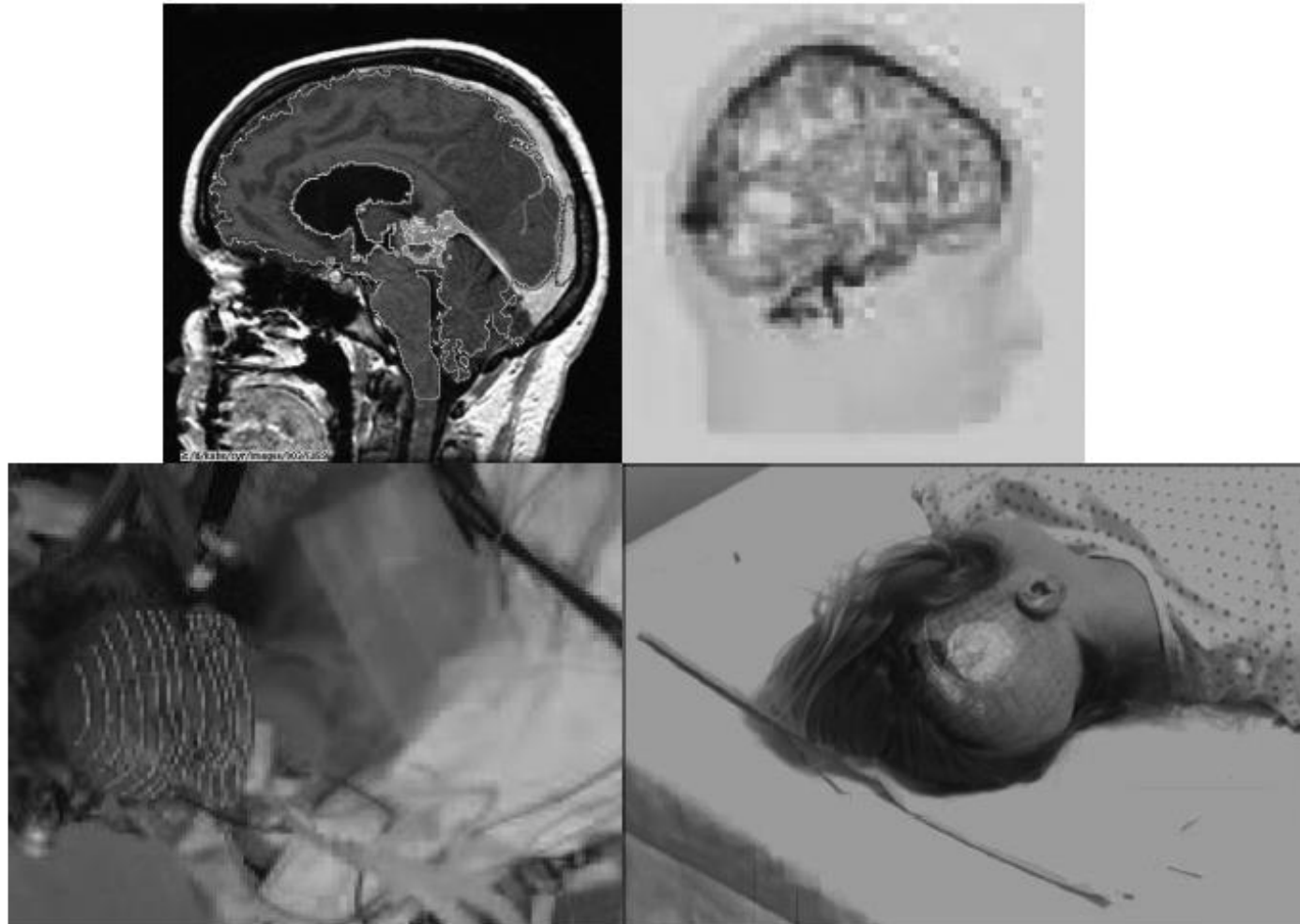
8 it.s

11 it.s

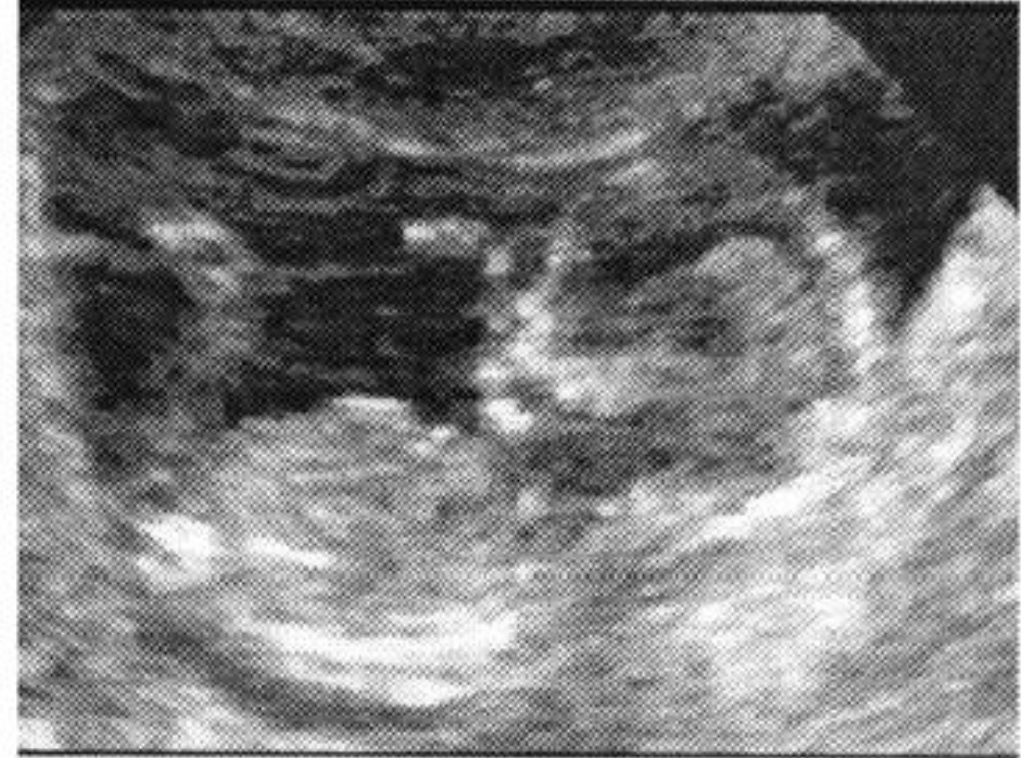
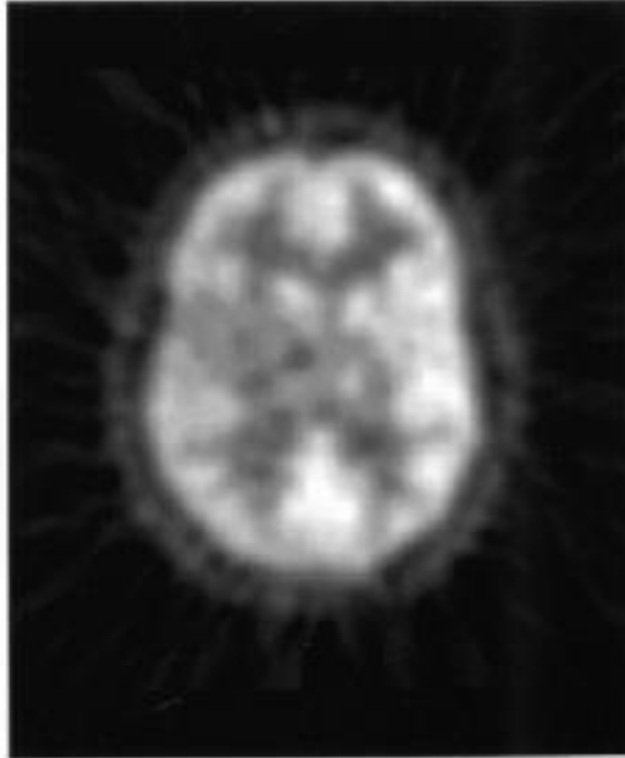
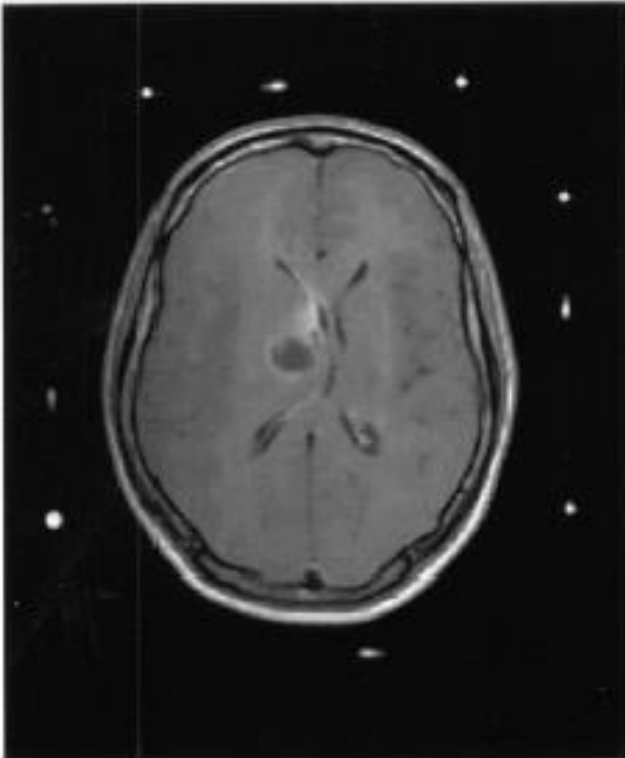
Original

Converged

single slice of MRI data with an automatically acquired segmentation overlaid



Images obtained with three different imaging modes



Conclusion

Registration is key technique

Object
detection++

Ample accurate
algorithms

Real time
applications



Q&A

Contact



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