Vehicle Recognition System

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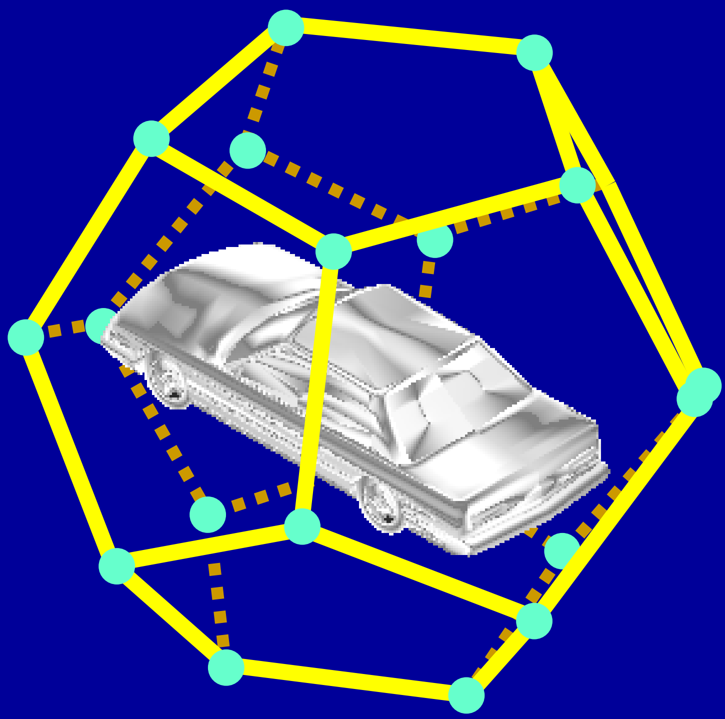
Recognition Engine Steps

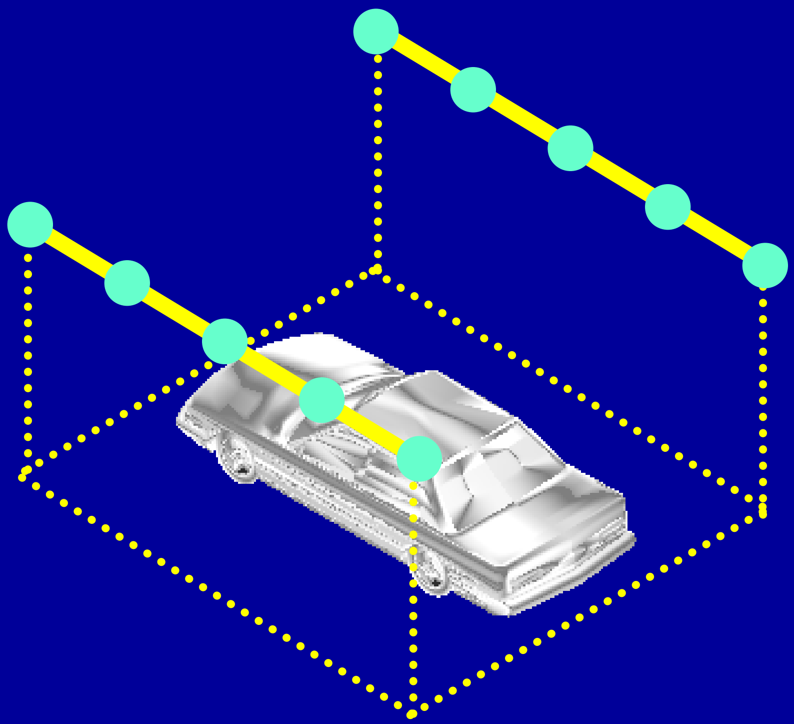
- Acquire range images
- Determine regions of interest (see Kanu)
- Local surface estimation
- Surface reconstruction
- Affinity measure
- Spectral Clustering: Normalized cuts
- Graph matching

Range Image Acquisition

- Model building



- Testing



Local Surface Estimation

- **What:** (1) Estimate the local surface characteristics (2) at given locations
- **Why:**
  - (1) Vehicles are made up of large low-order surfaces
  - (1) Look for groups of points that imply such surfaces
  - (2) Our sets of range images are BIG
    - (tank from 10 views has over 220,000 range points)
- **How…**

Local Surface Estimation:

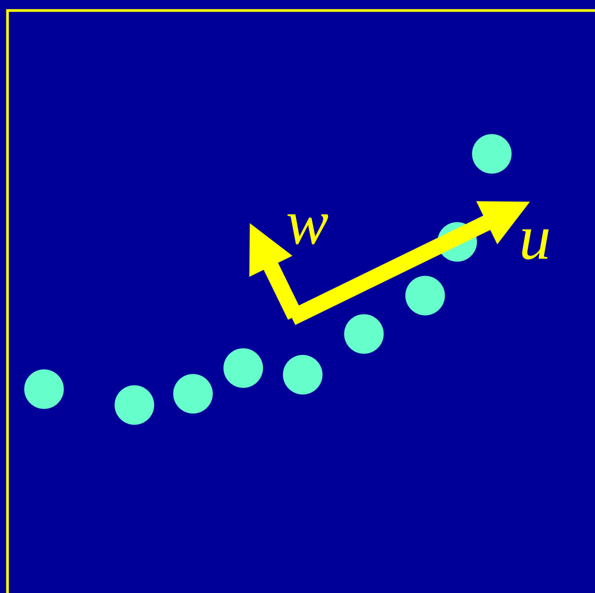
Point Set Selection

- In the region of interest…
- Collect range image points into cubic voxel bins
  - (*32x32x32mm* right now)
- Discard bins that have:
  - Too few points
  - Points that do not represent a biquadratic surface well
- Retain only the centroids of the bins and their surface fits

Local Surface Estimation:

Biquadratic Patches

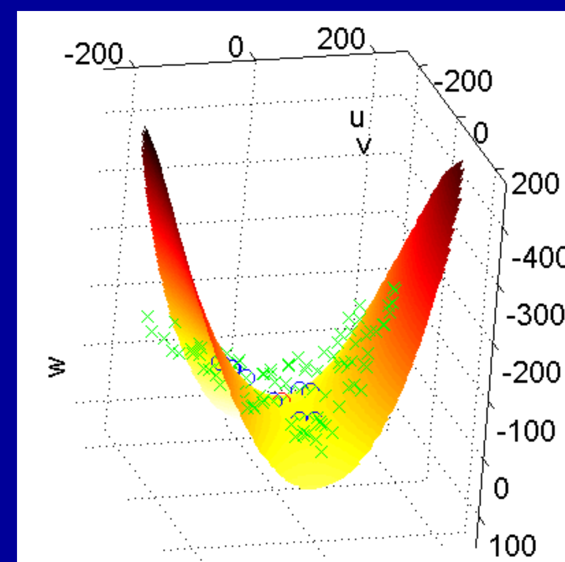
- PCA → local coordinate system



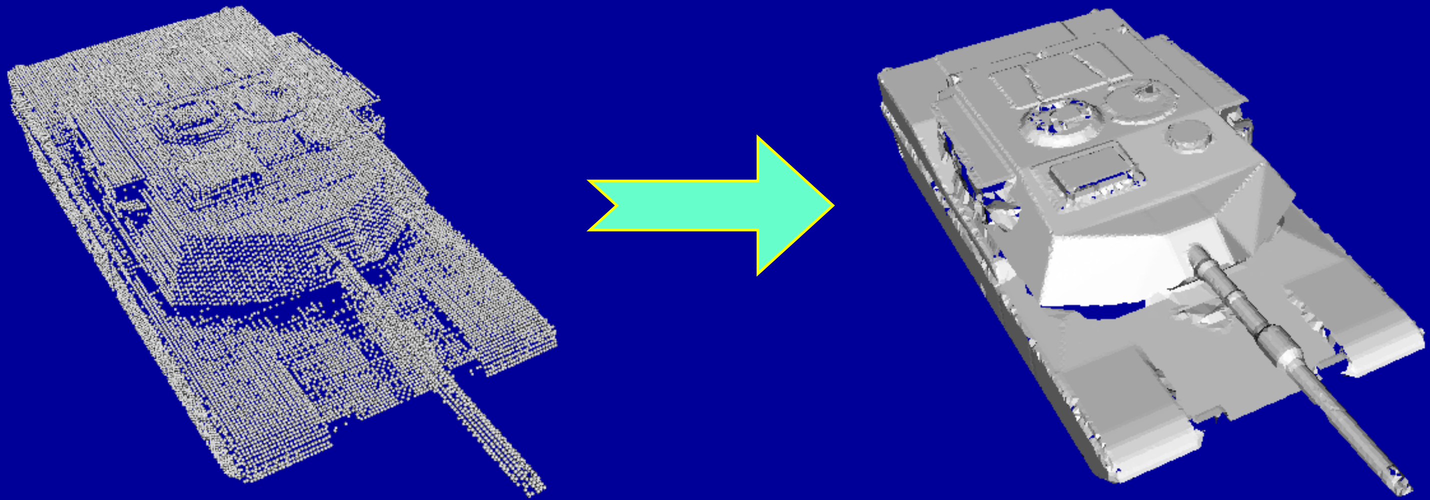
- Least squares biquadratic fit:

$f(u,v) =$

$$a_1u^2 + a_2uv + a_3v^2 + a_4u + a_5v + a_6$$



Surface Reconstruction



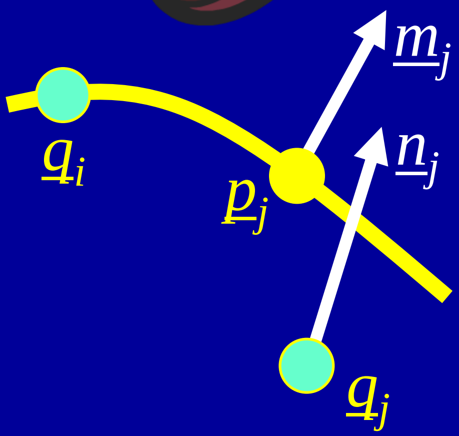
See last quarter's presentation for details on cocone

Affinity

- **Quasi-Definition:** Affinity $\propto$ probability that two mesh points were sampled from the same low-order surface
- **Why:** Can use grouping algorithms to segment the mesh (to make recognition easier)
- **Our formulation…**

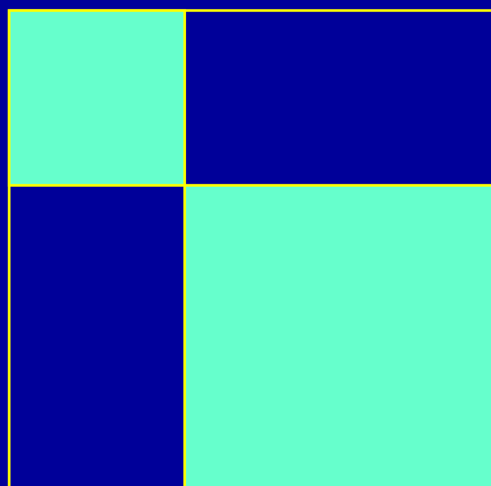
Affinity, Cont'd.

- **Basic formulae:**
  - Symmetric affinity: $A_{ij} = min\left(a_{ij}, a_{ji}\right)$
  - Asymmetric affinity: $a_{ij} = p_{ij} n_{ij} d_{ij} f_{ij}$
- **Where...**
  - σ_i is the RMS^2 biquadratic fit error
  - $\sigma = \sum_{i=1}^{N} \sigma_i / N$
  - $p_{ij} = e^{-|\overline{p}_j - \overline{q}_j|^2/\sigma^2}$
    - $\overline{p}_j$ = the projection of point $\overline{q}_j$ onto i's surface estimate
  - $n_{ij} = e^{-\left((\overline{m}_j.x - \overline{n}_j.x)^2 + (\overline{m}_j.y - \overline{n}_j.y)^2\right)/4\sigma^2}$
    - $\overline{m}_j$ = the surface normal at $\overline{p}_j$, using surface i
    - $\overline{n}_j$ = the surface normal at $\overline{q}_j$, using surface j
  - $d_{ij} = e^{-2|\overline{q}_i - \overline{q}_j|^2/r^2}$
  - $f_{ij} = e^{-\sigma_i^2/\sigma^2} e^{-\sigma_j^2/\sigma^2}$

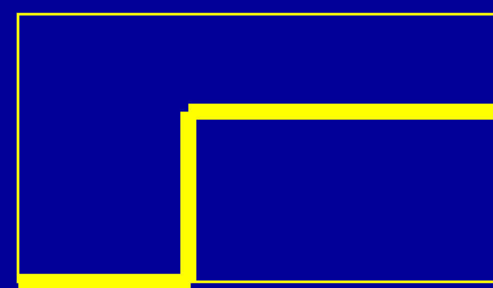


Spectral Clustering

- A_{ij} is "block diagonal" → Non-zero elements of the 1st eigenvector define a cluster [Weiss,Sarkar96]



A_{ij}

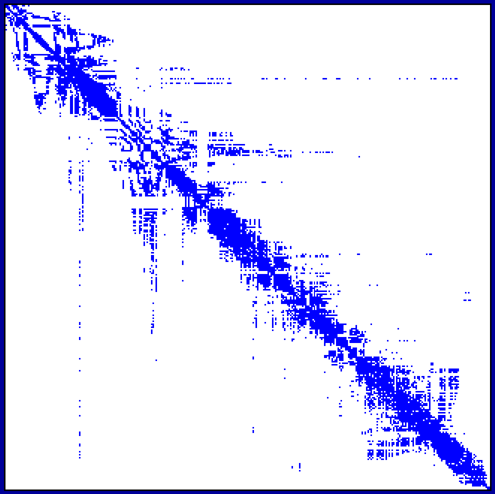


y_1, where

$Ay_i = \lambda_i y_i$

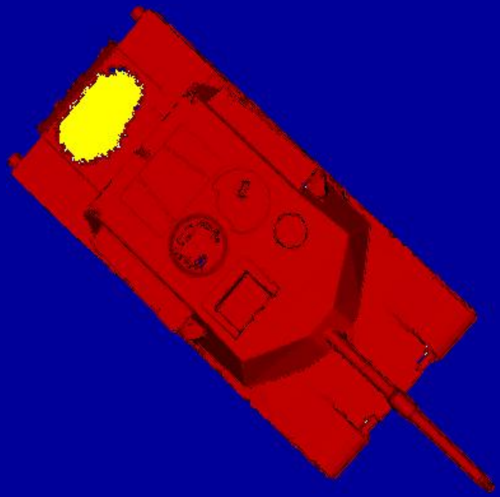
Spectral Clustering, Cont'd.

- Example using our data…



A_{ij}

y_1, where $Ay_i = \lambda_i y_i$



1st Cluster

Spectral Clustering:

Normalized Cuts

- Tend to get disjoint clusters
- Need to balance clustering and segmentation

$$D_{ii} = \sum_j A_{ij}$$
$$(D - A)y_i = \lambda_i D y_i$$

Graph Matching

- For each model *i*
  - R: For each unused object segment *s*
    - For each (model segment *i.t* , NULL segment)
      - Compute penalty for matching *s* to *i.t* + all previous matches made
      - Save this match if it’s better than any other
      - Recurse to R
  - Save the best matching of model and object segments for model *i*
- Choose the model with the best match

Graph Matching:

Segment Attributes

- Unary attributes *(for comparing one object segment to one model segment)*
  - Segment area
  - Mean and Gaussian Curvature
    - (from a new biquadratic fit to the voxel points participating in the segment)
  - "Distinctiveness"
- Binary attributes *(for comparing a pair of object segments to a pair of model segments)*
  - Centroid separation
  - Angle between normals at the centroid

Further Reading

- Y. Weiss *et al*. "Segmentation using eigenvectors: a unifying view". *ICCV*: 975-982, 1999.
- S. Sarkar and K.L. Boyer. "Quantitative measures of change based on feature organization: eigenvalues and eigenvectors". *CVPR* 1996.
- J. Shi and J. Malik. "Normalized Cuts and Image Segmentation". *PAMI*: 888-905, 2000.