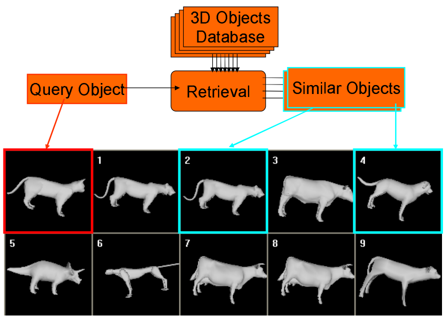
3D object retrieval



Related areas

- Computational geometry
- Computer vision
- Computer graphics

In three dimensions

- Extending methods of comparing polygonal curves is non-trivial.
  - No arc-length parameterization, no direction
  - "Polygon Soup" - no topological information
- Images - is the problem easier or more difficult?

Main issues

- Choice of features (signature)
  - Compact
  - Identify the object
  - Reflect similarity
- Choice of a distance measure

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Signatures

- Moments
- Histograms of statistics
- Shape distributions
- Sphere projection
- Surface decomposition
- Topological properties (Reeb graph)
- Lightfields
- Spherical harmonics

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Signature: moments

- The features are the shape moments

$$m_{pqr} = \int_{3D} x^p y^q z^r \, dxdydz$$

- Objects are sampled

$$m_{pqr} = \frac{1}{N} \sum_{i=1}^{N} x_i^p y_i^q z_i^r$$

- After applying normalization, the moments are computed, up to the pre-specified order

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Signature: histograms of statistics

- Normals
- Curvatures
- Cords
- Colors
- Materials
- Angles

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Signature: shape distributions

probability distribution samples from a *shape function* measuring geometric properties

- *A3* – measures the angle between 3 random points
- *D1* – measures distance between a fixed point and a random point
- *D2* – measures distance between 2 random points
- *D3* – measures the area of the triangle between 3 random points
- *D4* – measures the volume of the tetrahedron between 4 random points

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Signature: sphere projection

Idea: Measure the amount of "energy" to deform an object to sphere: $E = \int_{dist} \vec{F} d\vec{r}$

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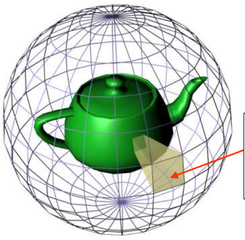
Computing the signature

Sphere surface is uniformly sampled

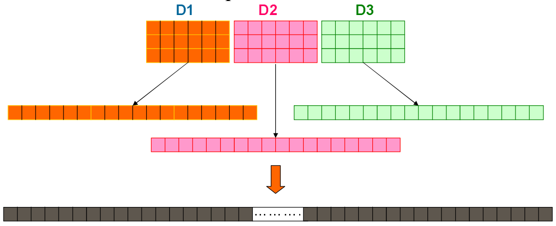


For each sample 3 values are calculated:

- D1 - Distance from object to sphere
- D2 - Distance from sphere to object
- D3 - Radii Variance

Signature concatenation

Three matrices are produced

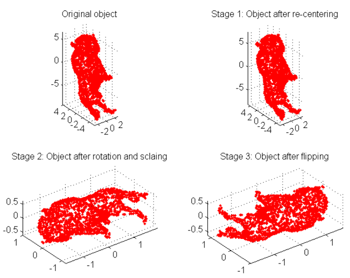


Feature vector = Signature

Normalization

- **Goal** - similarity measure should be invariant to spatial position, scale and rotation
- The first moments represent the object's center of mass: $[x_i, y_i, z_i] \leftarrow [x_i - m_{100}, y_i - m_{010}, z_i - m_{001}]$
- The second moments represent the object's rotation and scale: $U \Delta U^T = SVD(M)$
- The orientation of the object is determined relative to each axis

Example



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Signature comparison

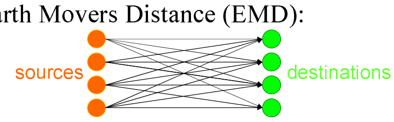
- Euclidean Distance:

$$d(p,q) = (p-q)(p-q)^T$$

- Quadratic Form Distance:

$$d(p,q) = (p-q)A(p-q)^T$$

- Earth Movers Distance (EMD):



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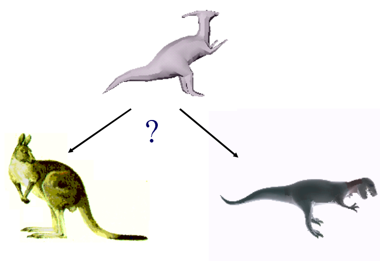
Problem



"Similarity is in the eye of the beholder"

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Main issues

- ❑ Choice of features (signature)
- ❑ Choice of a distance measure
- ❑ An adaptation rule for the distance measure

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Similarity measure

Consider what the human user has in mind

$\Rightarrow \; d(D_x, D_y) = [x-y]^T W[x-y] + b$

Reflects similarity, amenable to adaptations

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Relevance feedback

- ❑ Given an object, the system searches the database for similar objects.
- ❑ The user marks a subset of the results as relevant or as irrelevant.
- ❑ The distance function is updated and another iteration may be conducted.

Each user may get different objects as the closest to the chosen one

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Iterative refinement of the search

- Distance adaptation is done by recalculating distances, based on the user's preferences.
- The new distance to the relevant results must be small and to the irrelevant results - large.

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Learning

- The constraints posed on the weight function:

$$k=1,2,\ldots n_G,\quad d(D_O,D_{G_k})=[O-G_k]^T W[O-G_k]+b\le 1$$
$$l=1,2,\ldots n_B,\quad d(D_O,D_{B_l})=[O-B_l]^T W[O-B_l]+b\ge 2$$

- Denote the diagonal by ω

$$k=1,2,\ldots n_G,\quad d(D_O,D_{G_k})=[O-G_k]^2\omega+b\le 1$$
$$l=1,2,\ldots n_B,\quad d(D_O,D_{B_l})=[O-B_l]^2\omega+b\ge 2$$

- This is a classification problem between $[O-G_k]^2$ and $[O-B_l]^2$

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Which solution is the best?

The maximal margin separation is achieved by the ω with the smallest norm

Minimize $\|\omega\|^2$
Subject to:
$k=1,2,\ldots n_G,\ d(D_O,D_{G_k})=[O-G_k]^2\omega+b\le 1$
$l=1,2,\ldots n_B,\ d(D_O,D_{B_l})=[O-B_l]^2\omega+b\ge 2$
$\omega\ge 0$

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Experimentation

- Database: over 1000 VRML objects
- Pre-processing:
  - Objects are sampled with 10,000 points
  - Objects are normalized
- Signatures: A feature vector of the moments (4-7) is computed for each object

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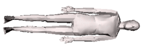
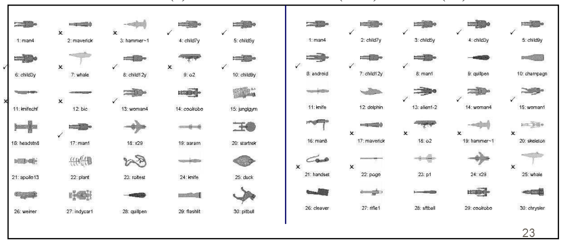
Example - figures



First iteration (9) Last (third) iteration (13)



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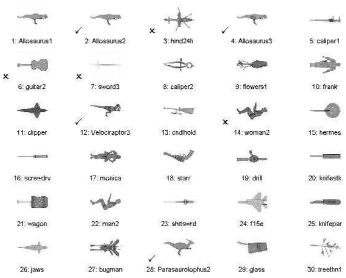
Dinosaurs - 1st iteration



5 Dinosaurs

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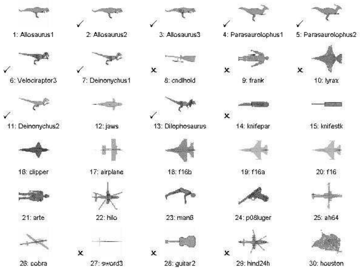
Dinosaurs - 2nd iteration



9 Dinosaurs

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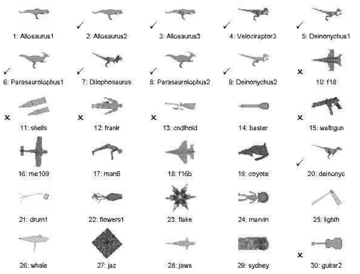
Dinosaurs - 3rd iteration



10 Dinosaurs

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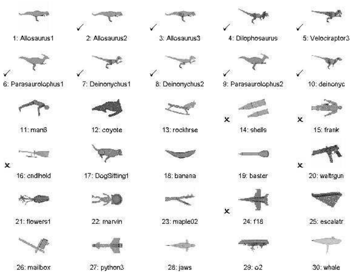
Dinosaurs - 4th iteration



10 Dinosaurs

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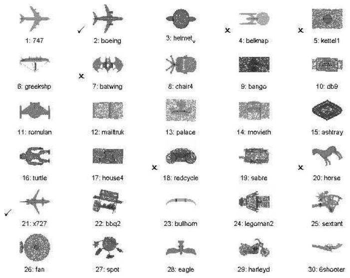
Airplanes - 1st iteration



3 Airplanes

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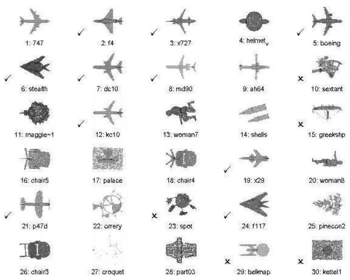
Airplanes - 2nd iteration



11 Airplanes

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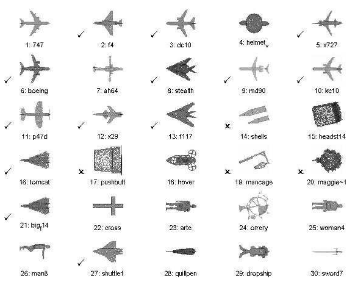
Airplanes - 3rd iteration



14 Airplanes

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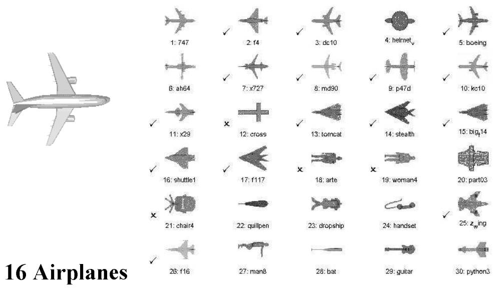
Airplanes - 4th iteration



16 Airplanes

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How to perform a comparative study?

- Choose a large database, classified into categories
- Automatic Evaluation:
  - Each classified model is used as a query
  - Relevant = same class as the query
  - Average over all the queries

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Evaluation methods

- Nearest neighbor
- Precision/Recall measurements
- First/Second tier
- Cumulated gain based measurements

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Precision/recall

- Let C = models in query's class
  S = set of retrieved models
  I = intersection of S and C
- $R = \frac{|I|}{|C|}, P = \frac{|I|}{|S|}$
- F-measure $F = \frac{2PR}{P+R} = \frac{2}{\frac{1}{P}+\frac{1}{R}}$

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First/Second tier

- Measure the success percentage among the first k retrieved objects
- First: k = (size of model's class)
- Second: k = 2X(size of model's class)

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Discounted Cumulative Gain

Gained value with discount factor

Gain vector: Gi=1 if object in the same class

Cumulated gain vector with discount factor:

$$DCG_i = DCG_{i-1} + G_i / \log i$$

$$DCG = \frac{DCG_k}{1 + \sum \frac{1}{\log(j)}}$$

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