Global Shape Matching

Section 3.2: Extrinsic Key Point Detection and Feature Descriptors

The story so far

Problem statement

- Given pair of shapes/scans, find correspondences between the shapes

Local shape matching

- Solves for an alignment assuming that pose is similar or motion is small between shapes / scans
- Like "tracking" of motion in this respect

In this session: Global Shape Matching

What is Global Matching?

Problem statement

- Find the globally optimal correspondences between a pair of shapes
- Search space = set of all possible correspondences
- Same sense as local minimum vs. global minimum in optimization

- Don’t get confused with **global registration**
  - “Global registration” is commonly used to refer to aligning *multiple scans* together to make a single shape

Local vs. Global

Local Matching vs. **Global Matching**

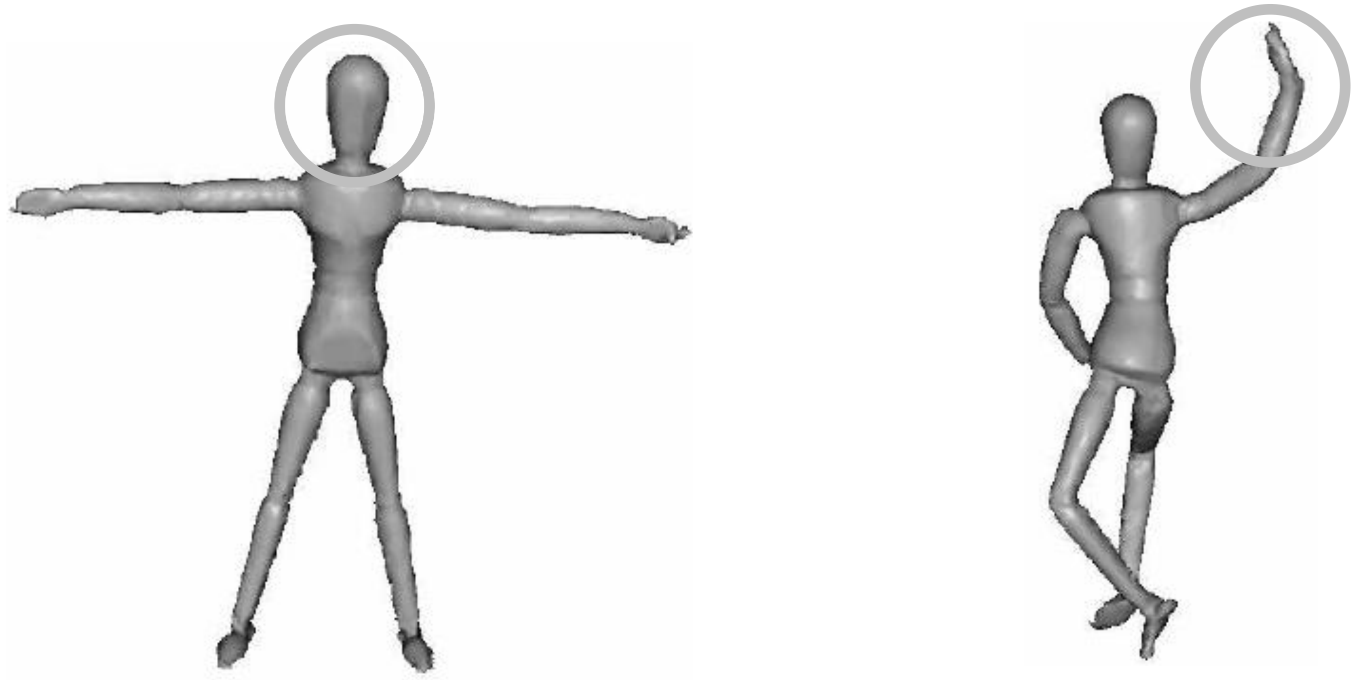
- Search in space of transformations, minimize alignment energy
- Relatively small search space… relatively easy

- Search in the space of *all possible correspondences*, minimize alignment energy
- Incredibly large search space… nearly impossible?

➔ Features to the rescue!

Our eyes recognize features

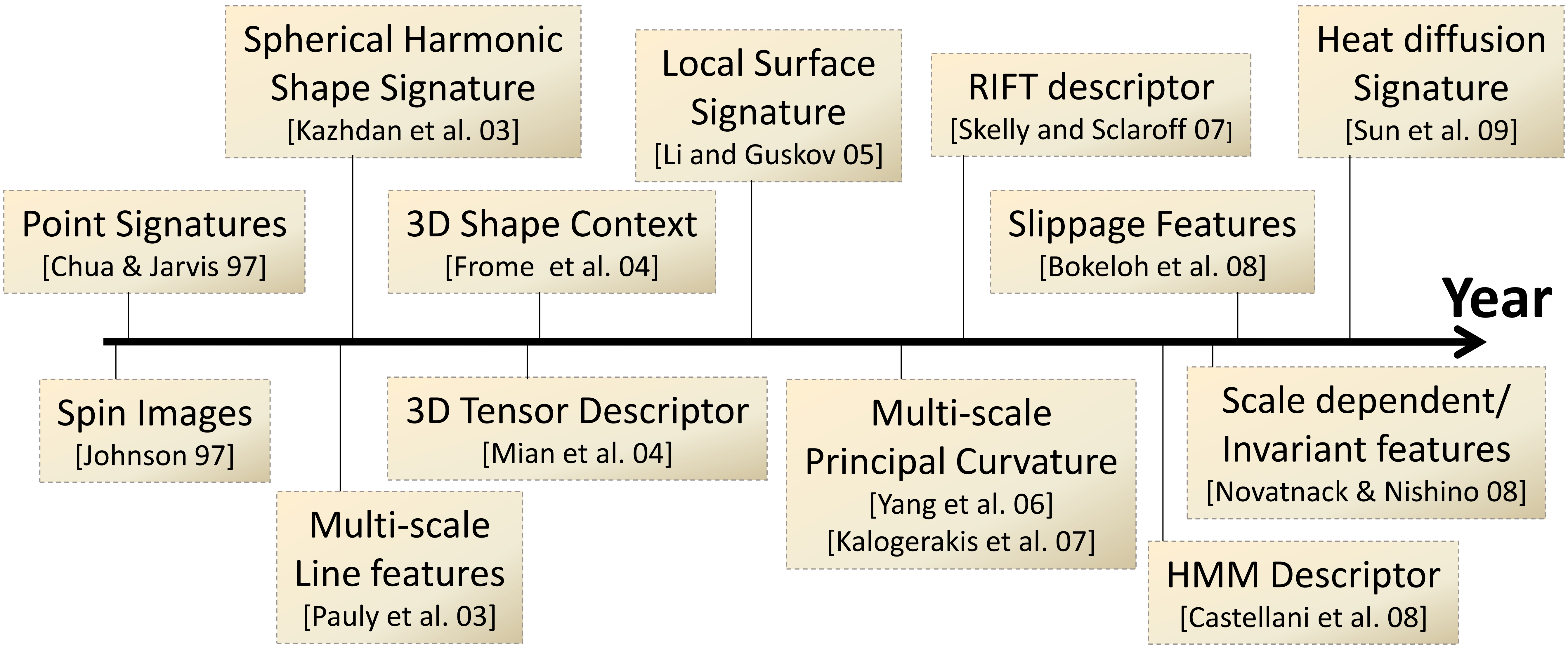
Face ≠ Arm



- Why? It looks different!
- Can dramatically reduce space of possible solutions
- How can we directly compare the geometric content to recognize similarity/dissimilarity?

Types of Features

Welcome to the world of feature descriptors..



- Many more exist… possibly with different objectives
  - ex) Matching whole shape vs. local patches

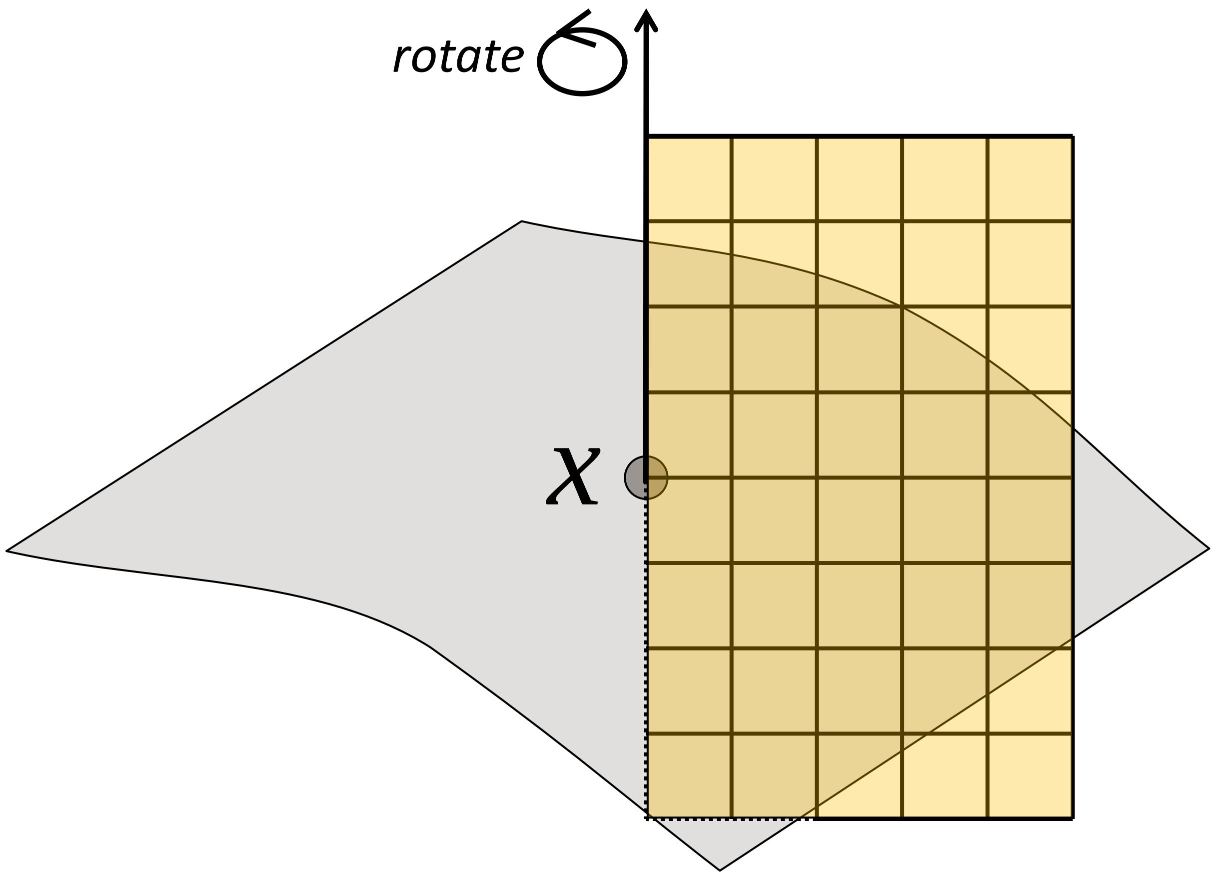
An Example: Spin Images

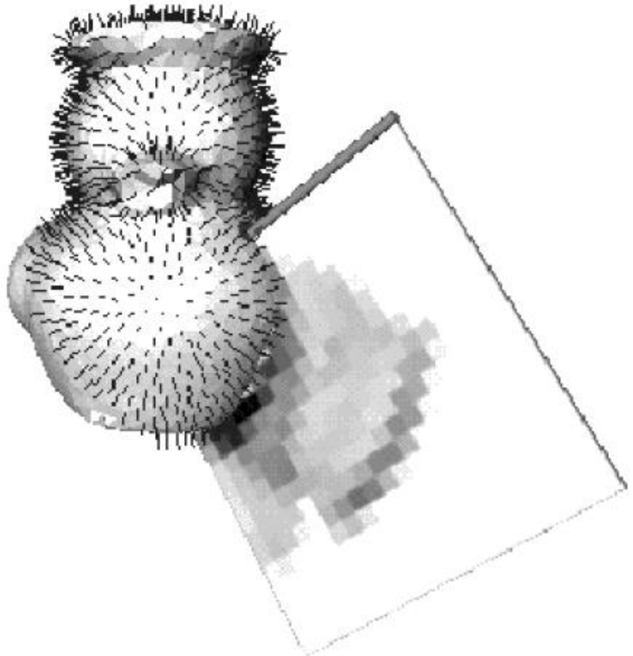
One of the earliest feature descriptors

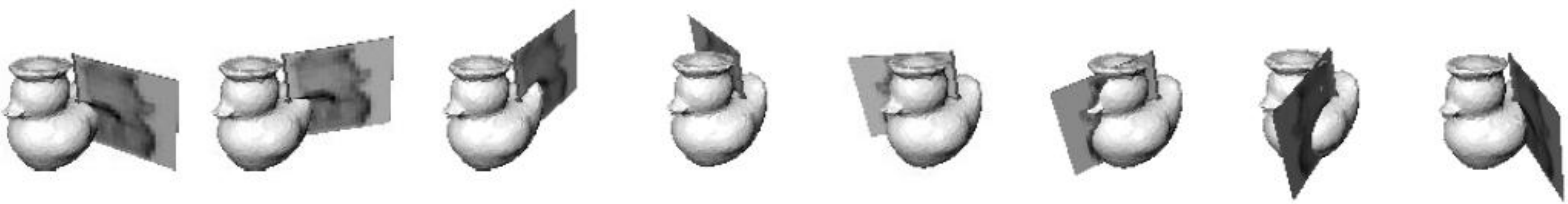
- Established, simple, well analyzed
- Clearly illustrates the process of how this type of recognition works
- Also illustrates potential problems & drawbacks common to any type of feature descriptor

Spin Image Construction

- Converts a local patch of geometry into an image, which we can directly compare to determine similarity





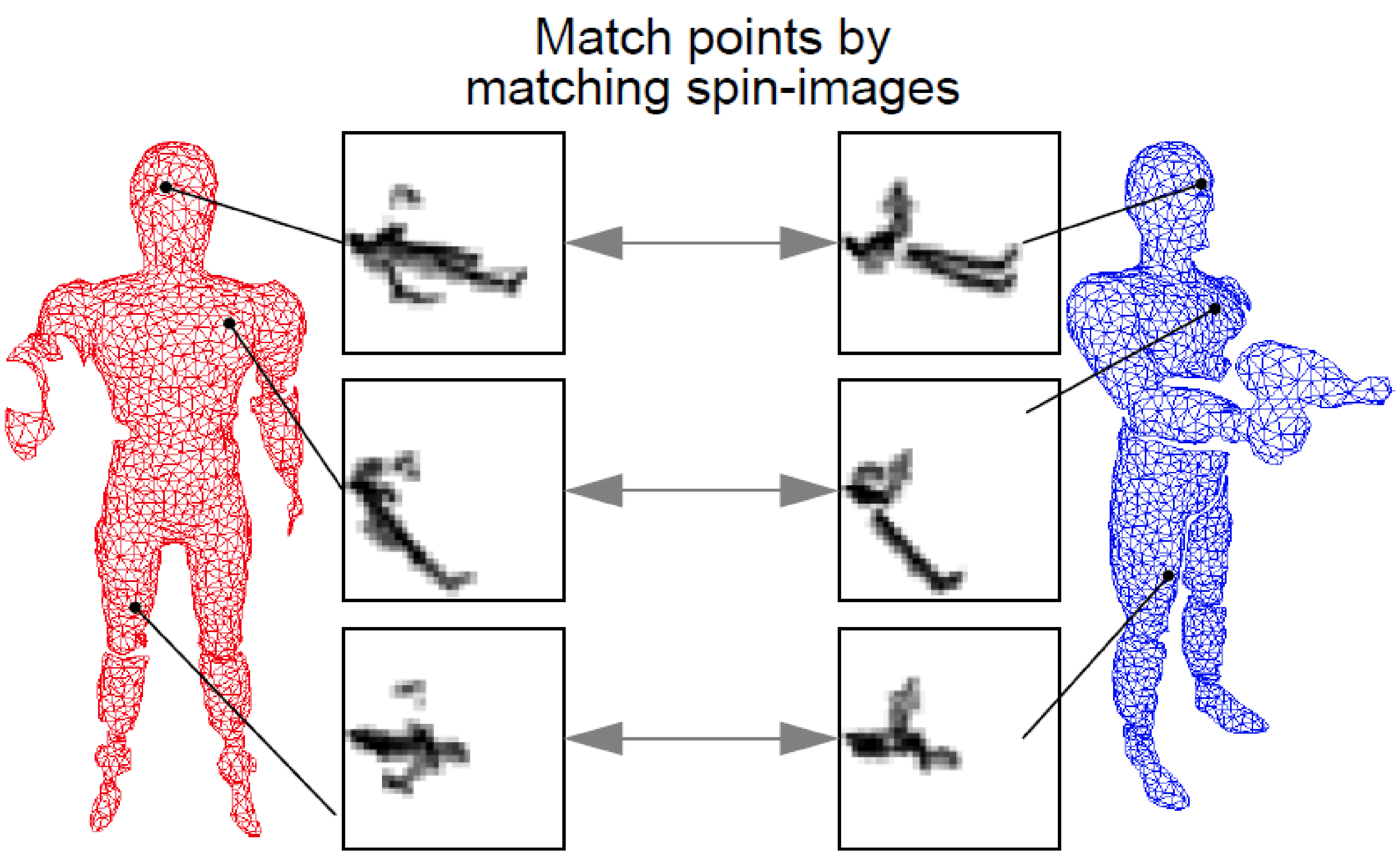


Images from [Johnson 97]

Spin Image Matching

Compare images directly to obtain similarity score

- Linear correlation coefficient → Similarity measure
- Compute only in “overlap”: when both bins have a value

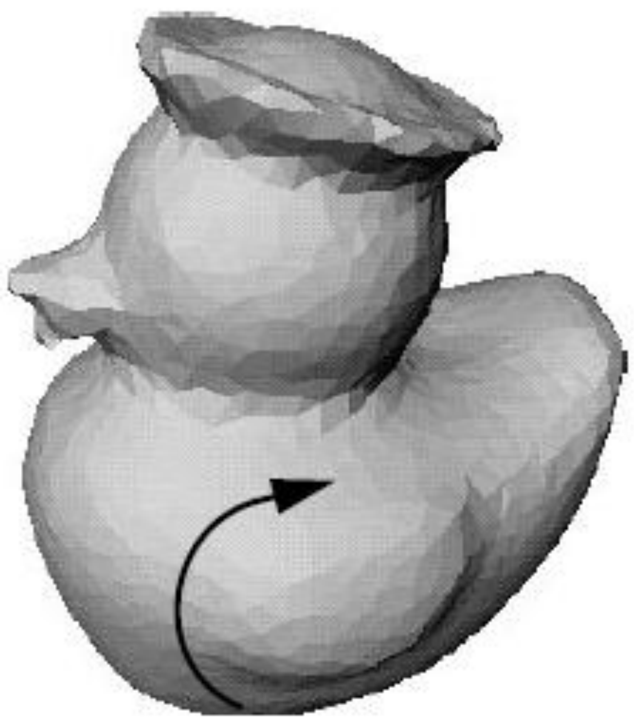


Images from [Johnson 97]

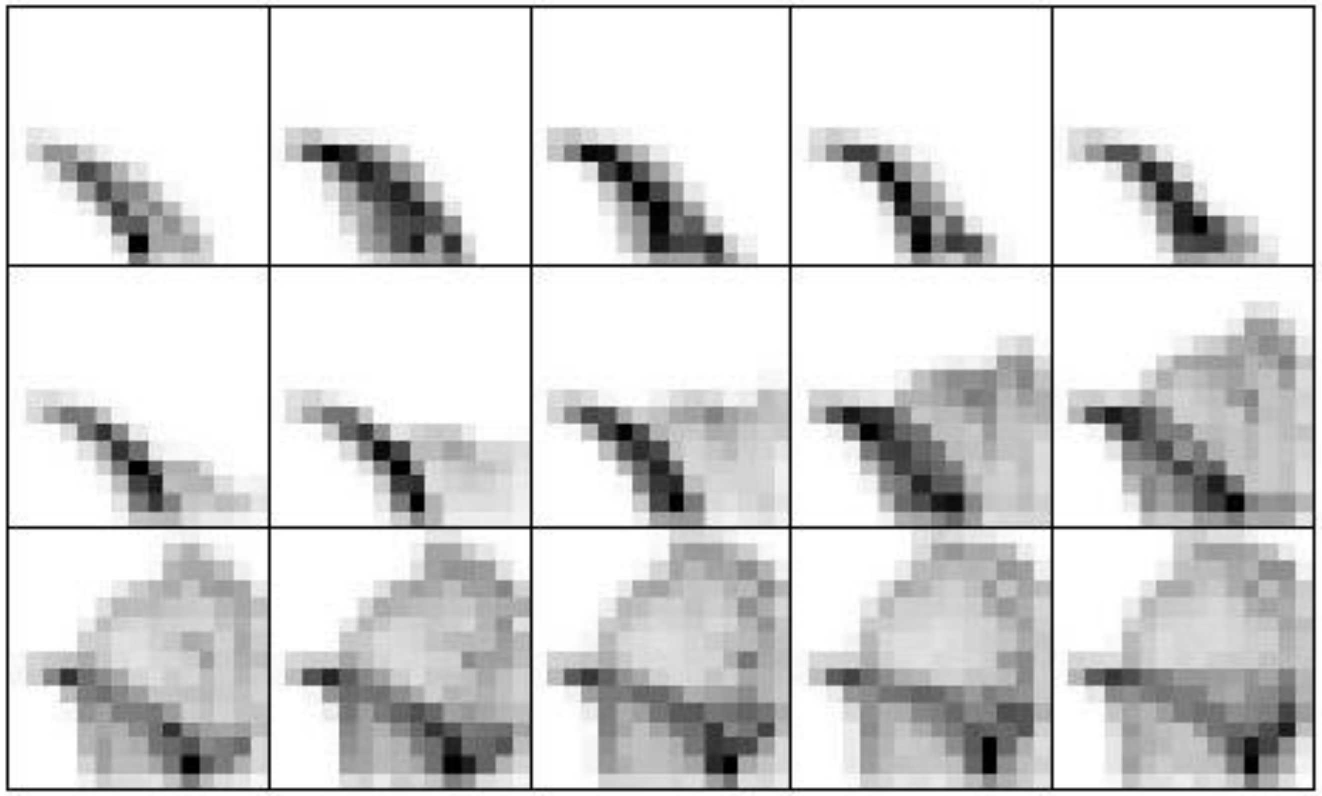
Compressing Spin Images

Spin images from the same model are similar

- Reduce redundancy with PCA compression
- Save space and matching time



Spin images generated from vertices along this curve

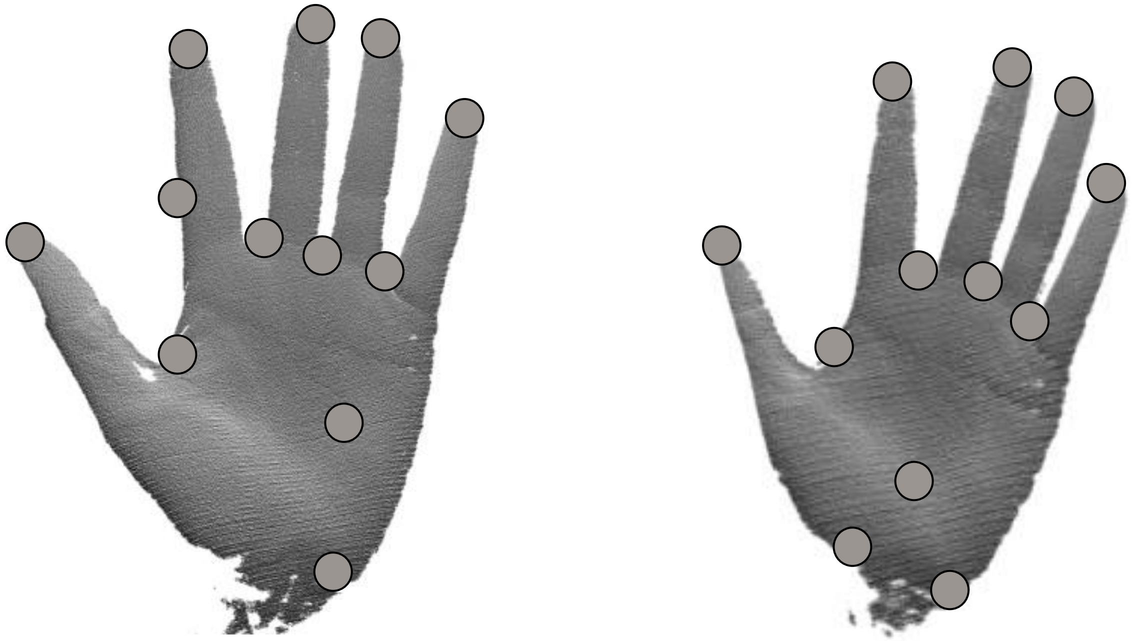


Images from [Johnson 97]

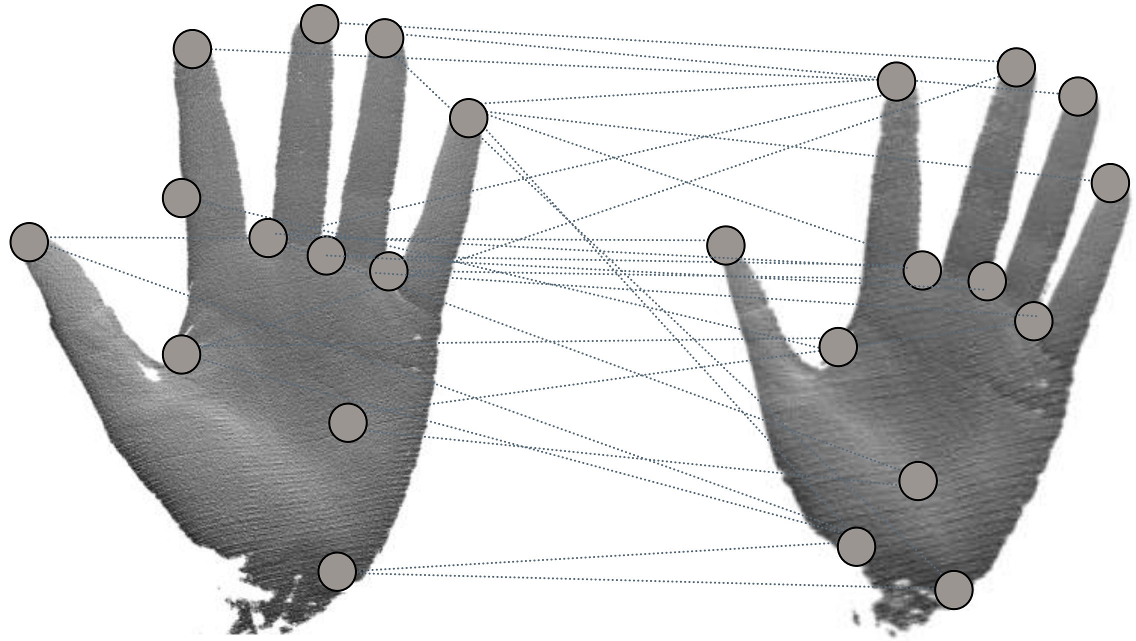
Spin Image Matching

Can detect geometrically similar parts

- But there are limitations



Detected feature points



Matched points

Problem #1: False positive/negative

False positive

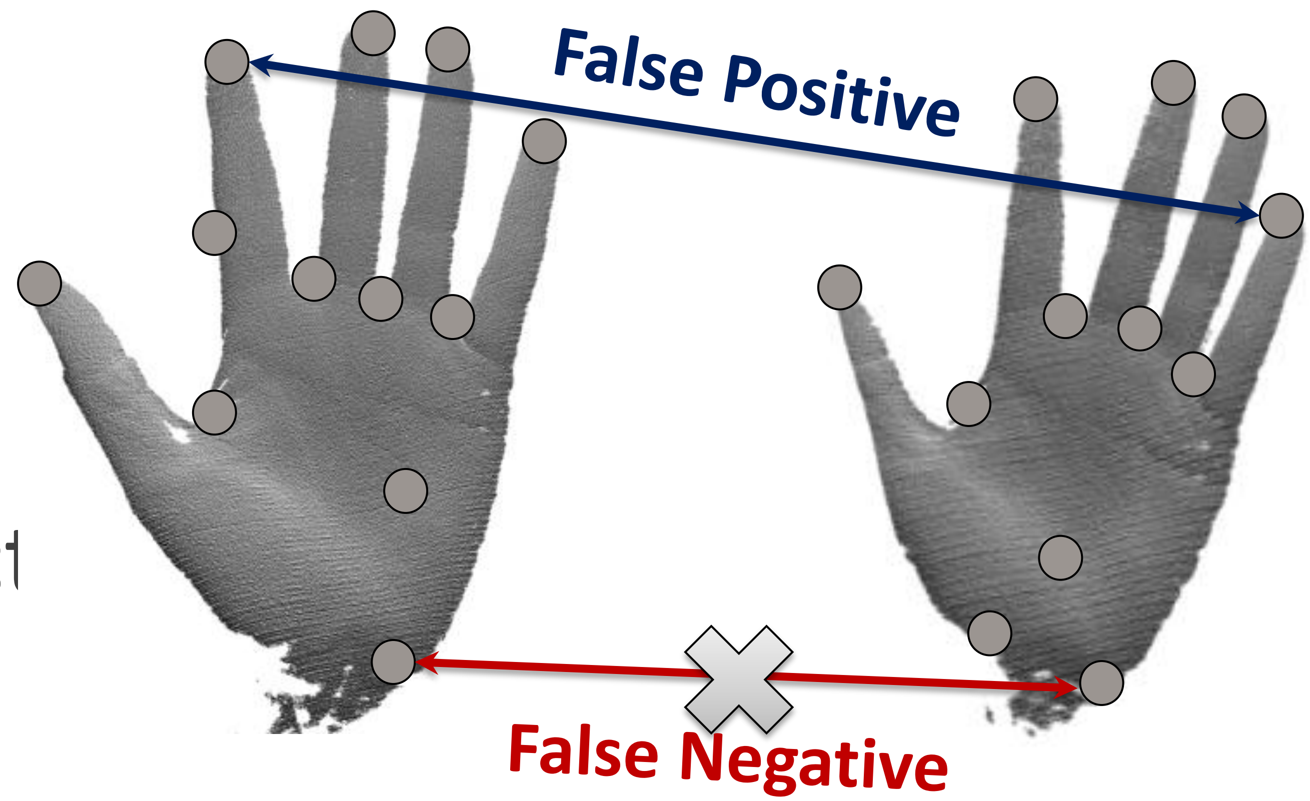
- Saying that two points match when in fact they don't

False negative

- Saying that two points don't match when in fact they do

Aka "noise" or "outliers"

- Occurs with any type of descriptor



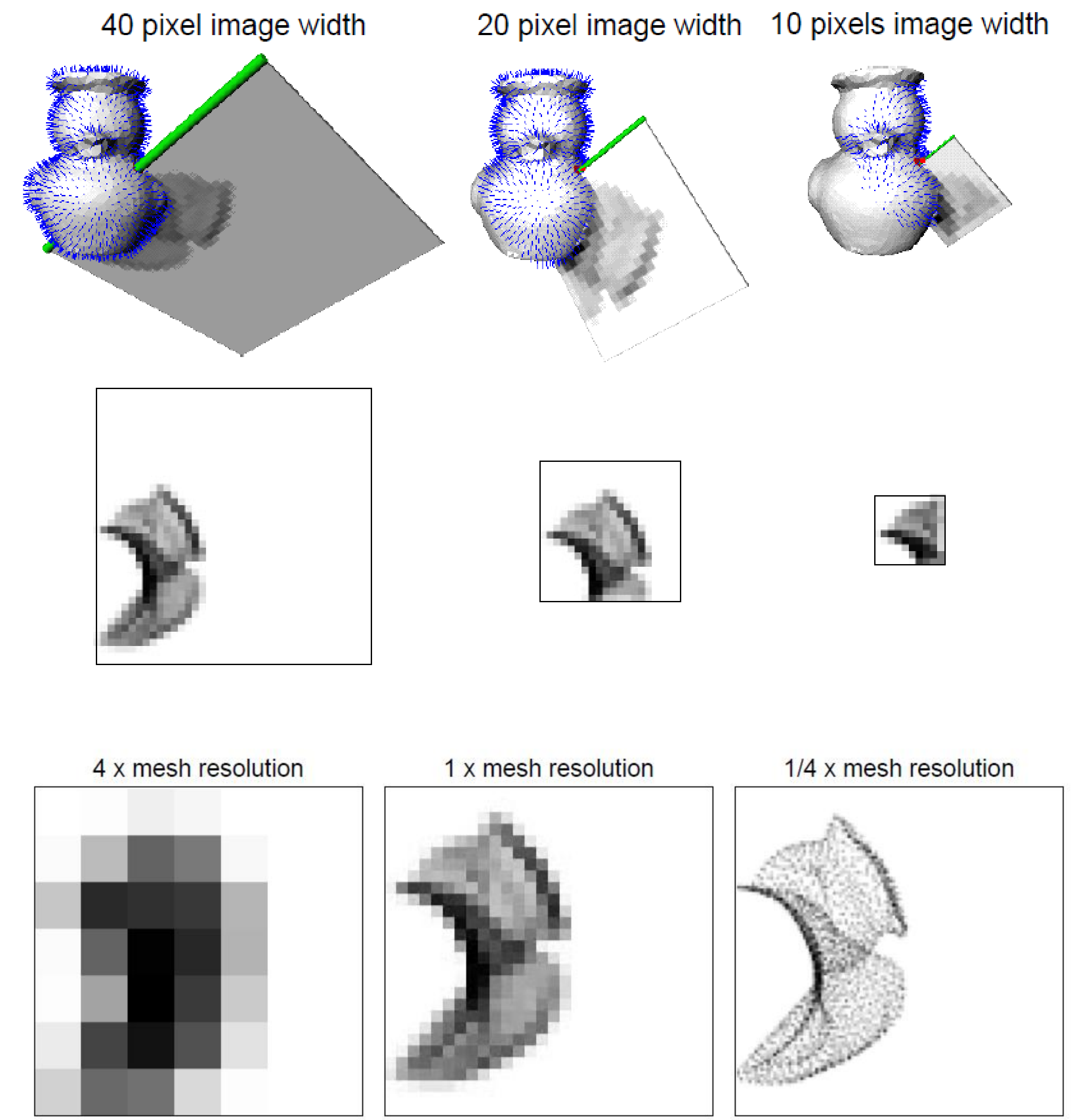
Problem #2: Parameter Selection

Examples of parameters for spin images

- Bin size
- Image width
- Support angle
- Mesh resolution

How to pick the best parameters?

- Fortunately well analyzed for spin images
- Others are studied/analyzed to varying degrees



Images from [Johnson 97]

Problem #3: Non-unique patches

What to do in flat / spherical / cylindrical regions?

- In this case, the region is not "unique" or distinctive
- Does it make sense to compare such regions?
  - Increasing the scale/support

Use multi-scale features, select scale automatically

Use "Global" features

- **e.g. heat diffusion signature**

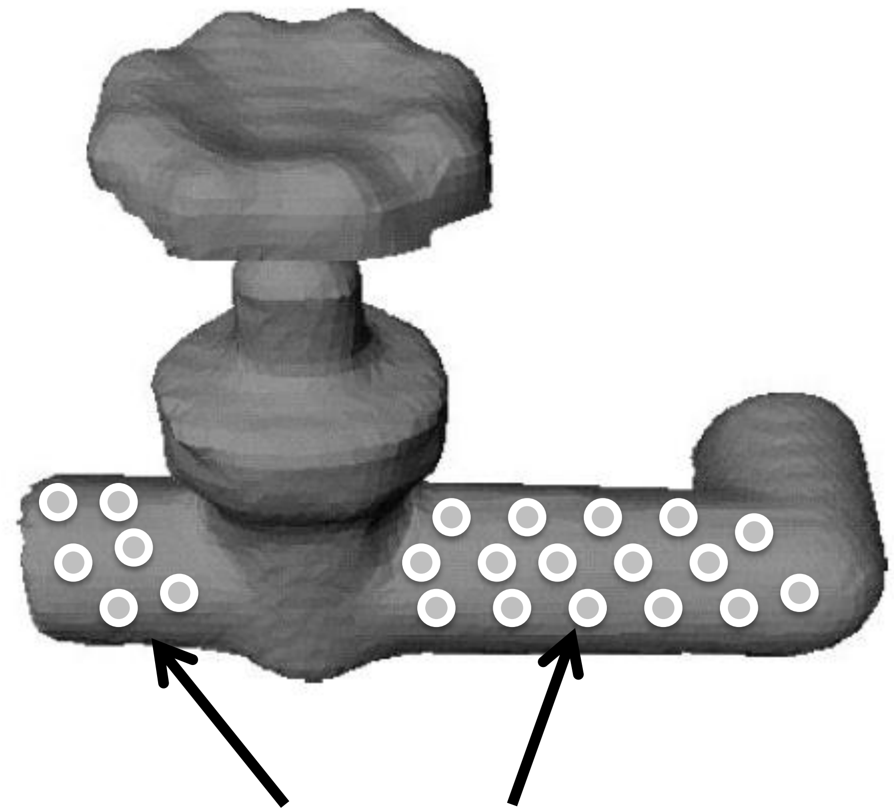


Image from [Johnson 97]

Conclusion

Feature descriptors

- Very useful for narrowing down search space
- Does not solve the problem completely
- Additional optimization in the (reduced) search space is needed → explored in the next few talks!