3.1 Introduction to geometric key point detection and feature descriptors

What is Global Matching? • Feature Descriptors
The story so far

Problem statement

- Given pair of shapes/scans, produce an alignment

Local registration

- 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 matching
What is Global Matching?

Problem statement

• Find the globally optimal alignment 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...

- Spherical Harmonic Shape Signature [Kazhdan et al. 03]
- Local Surface Signature [Li and Guskov 05]
- RIFT descriptor [Skelly and Sclaroff 07]
- Heat diffusion Signature [Sun et al. 09]
- Spin Images [Johnson 97]
- 3D Shape Context [Frome et al. 04]
- Slippage Features [Bokeloh et al. 08]
- 3D Tensor Descriptor [Mian et al. 04]
- Multi-scale Principal Curvature [Yang et al. 06] [Kalogerakis et al. 07]
- Scale dependent/Invariant features [Novatnack & Nishino 08]
- Multi-scale Line features [Pauly et al. 03]
- HMM Descriptor [Castellani et al. 08]

- 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

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 in 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
Problem #3: Non-unique patches

What to do in flat/spherical/cylindrical regions?

- In this case, the region is not “unique” or distinctive
- Doesn’t make sense to compare such regions..
- Or does it?
  - Increasing the scale/support

- Multi-scale features, select scale automatically
- “Global” features – ex) heat diffusion signature
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!