Scene Analysis From Range Data

Unsupervised Discovery of Categories

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Outline

• Classification
• Features
• Learning
• Experiments
• Summary
Classification

- Goal: Categorize objects in 3D range data
- Requirement: No information about classes
Classification

- Interpret object classes as feature distributions
- Infer the object's class

![Bar charts showing feature distributions for different classes: Round, Flat, Angular.](image)
Given a number of data segments, can we find the category distributions without further information?
Outline

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Features - Spin Images

- Introduced by Andrew Johnson
- Description of the local environment of a point
- Coordinate system aligned to surface normal
Features - Spin Images

• Robust to
  – Shape variation
  – Occlusion
  – Clutter
Features - Spin Images

- Robust to
  - Shape variation
  - Occlusion
  - Clutter
Features - Spin Images

- **Parameters**
  - **Support Distance** (top)
  - **Raster Resolution** (middle)
  - **Discretization Resolution** (bottom)
We now consider the surface normals of all points instead of point counts, we use the average angle. Same parameters as for standard spin images.
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Learning

- Probabilistic framework: latent Dirichlet allocation
- Introduced by David M. Blei in 2003
- Unsupervised: No class information necessary
- No explicit distance measurement necessary
- Category discovery from feature co-occurrence
Latent Dirichlet Allocation

Plate Notation:
- Unobserved Variable
- Observed Variable
- Sample Contained Variables X Times
Latent Dirichlet Allocation

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- Unobserved Variable
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Latent Dirichlet Allocation - Example
Goal

• **First Goal**: Infer most probable topic assignments for all features in a scene from co-occurrence

• **Second Goal**: Infer the feature distributions of the categories (to apply to unseen data)
Using Bayes' rule to determine the probability of classification:

\[ P(z \mid w) = \frac{P(w \mid z) P(z)}{P(w)} \]

- All class assignments
- All feature occurrences with assignment to data sets
- Intractable, involves \( T^N \) terms
Solution

• Use Markov chain Monte Carlo for approximation of $P(\mathbf{z} | \mathbf{w})$

1. **Initialization**: Assign random classes to all feature occurrences
2. **Gibbs Sampling**: Sample the class of each feature occurrence $i$ from $P(z_i | z_{\setminus i}, \mathbf{w})$
3. Repeat 2. until convergence
4. Use further samples to approximate $P(\mathbf{z} | \mathbf{w})$
5. Use the sample statistics to approximate $\phi$
High Level Algorithm

1. Scan scenes
2. Extract background
3. Spatial segmentation into scan segments
4. Learning of class assignments and definitions
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- **Experiments**
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Experiments

- Two corpora A/B of differing complexity
- Two/five object classes
- 12/39 scenes
- 31/82 scan segments
- Four parameters in feature feneration
- Two parameters for latent Dirichlet allocation
Experiments – Enhanced Spin Images

- Improved differentiation between object classes
- Increased similarity within object classes
Experiments – Enhanced Spin Images

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Experiments – Enhanced Spin Images

- Improved differentiation between object classes
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Experiments – Corpus A

Normalized Histogram Intersection for Discretization to 6 Values
Experiments – Corpus A

LDA
Latent Dirichlet Allocation

HC
Hierarchical Clustering
Experiments – Corpus B

• More Difficult Data:
  – Additional Object Classes
  – Similar Classes
  – Variation within Classes
Experiments – Corpus B

- Class differentiation is more difficult
- Feature parameters become very important
- Reliable parameter settings needed
Experiments – Corpus B

Feature Parameter Selection Results

- Feature Type: Enhanced Spin Images
- Support Distance: Small (10cm)
- Raster Resolution: Low (3x3 to 5x5)
- Discretization: 5 to 27 Values
Experiments – Corpus B

LDA Hyperparameter Selection Results

- Alpha < 1.0
- Beta < 0.4
HC Parameter Selection Results

- Four parameters for feature generation
- One clustering parameter (linkage type)
- No robust parameter settings found
Experiments - Results
Summary

- Shape-based discovery of object classes
- Clustering of feature distributions
- Spin image enhancements improve differentiation
- LDA greatly outperforms hierarchical clustering
- Highly satisfactory classification performance
References

- Griffiths, T. L. and Steyvers, M. “Finding scientific topics”, 2004
Thanks for Listening

Questions?