Motivation

› Where standard object detection fails
› Context helps – regular structures
› Some challenges:
Types of Symmetry

In 2D images we deal with
› Translation, reflection, rotation
› Groups – wallpaper, dihedral
Grouping Principles

Human perception priors are based on
– Proximity
– Similarity
– Reflection
– Continuation

Also known as Gestalt laws or symmetry in general.

We seek a language to describe such structures for computer vision.

Complexity – unknown number of components
Thesis Progress

› Weak Structure Model
  – **Simple** model implementing grouping principles
  – Window detection, sampling

› Spatial Pattern Templates
  – Learn **where** grouping principles apply
  – Facade parsing: semantic labels

› Reflection Symmetry Detection
  – More **general** approach resembling clustering
  – Improved inference engine, dihedral group
Weak Structure Model

- Can we infer global structure from local interactions?
- Markov Chain Monte Carlo sampling to find MAP solution
- Random Walk
- Reversible Jump
- Proposal Efficiency
- Convergence
Facade Image Parsing

- *Can we learn where grouping principles should be applied?*
- Dense Graphical Model
- More semantic labels and context
- New database for learning
Spatial Pattern Templates

› Binary and ternary terms
› Relative spatial location
› Approximate inference
Multiple Reflection Symmetry

› Correspondence matching problem
  – **Keypoints**: detected from corners and edges
  – **Primitives**: two corresponding keypoint(s)
  – **Components**: axes of reflection symmetry
  – **Groups**: clusters of components (dihedral)
Bayesian Modeling

› Data clustering problem
  – Gaussian mixture + outliers

› Target distribution
  = data model + allocation + priors

\[ p(X, Z, \theta, k) = p(X \mid Z, \theta, k) \, p(Z \mid \theta, k) \, p(\theta \mid k) \, p(k) \]

– \( X \) … data primitives with attributes
– \( Z \) … allocation of data points to components
– \( \theta \) … component and shape parameters
– \( k \) … complexity

› Bayesian choice
  – prior design requires some skills
Bayesian Inference

1. Model Selection
   - Consider multiple models with different complexity and choose one to maximize the posterior marginal
     \[ k^* = \arg \max p(k \mid X) \]
   - Integrate over parameters by MCMC sampling
     \[ p(k \mid X) \propto \sum_Z \int_{\theta} p(X, Z, \theta, k) \, d\theta dZ \]

2. Parameter Estimation
   - Determine the most probable parameters
     \[ \theta^* = \arg \max p(X, Z, \theta \mid k^*) \]
   - Use Stochastic EM to find locally optimal values

   › Inference Engine: LiSAEM
     - Efficient: improved mixing rate, ~10k samples needed
Multiple Reflection Symmetry

› General difficulties:
  – Multiplicity
  – Hierarchy

› Domain specific ambiguities:
  – Figure-Ground
  – Local-Global

Addressed with:
  ➢ Model selection
  ➢ Grouping priors
    ➢ Dihedral
    ➢ Objectness
  ➢ Compactness
Experimental Results

› Improved state-of-the-art results on reflection symmetry benchmarks (~10%)
Main Contributions

› Application of statistical methods for object counting new to computer vision
  – Parsimony by means of model selection
  – Learning without overfitting

› Minimal modeling principle
  – Simple language for consistent models

› Grouping priors
  – Components are not independent
  – Hierarchy of symmetries
Thank You

› Questions?
Questions

› What are the alternative models and their properties?
  – Complexity estimation
    › Bayesian Information Criterion \( \text{BIC} = n \cdot \ln(\hat{\sigma}_e^2) + k \cdot \ln(n) \)
      – Fixed penalty for increase of complexity
    › Multi-RANSAC
      – complexity estimation greedy or empirical
  – Symmetry modeling
    › Near Regular Textures – element unknown
    › Grammars – strong but restricted layout
    › Sequential inference – generally suboptimal
Questions

› Would larger datasets improve the results?
  – WSM, BMRS:
    › Yes, hyper-parameter learning would be possible on the next level
  – SPT:
    › Yes, now only limited number of samples used for training (MPL)
    › Results from CNNs suggest large data are useful
  – Computationally demanding
Questions

› Hierarchical Bayesian model