

Joint Nonparametric Alignment for Spatial Gene Expression Pattern Analysis of Drosophila Imaginal Discs

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## Some Basics Terms



- Drosophila Melanogaster
  - Fruitfly (very popular in gene expression studies)
- Nonparametric methods
  - Machine learning methods that use a set of examples as the learning primitives
- Spatial Gene Expression Patterns
  - Usually the micro array gene expression data is a time series with information about lots of genes but no spatial resolution
  - Patterns of spatial expression are considered to show the effect of a gene on a cell's evolution and behavior
- Imaginal Discs
  - Primordial tissues that will go on to become part of the exoskeletons of the Fruitfly
  - Separated in embryogenesis

#### So how do imaginal discs look like?



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#### Motivation



 High throughput systems require automatic alignment and simple processing pipeline

- Manual curation is expensive
- Align the imaginal disc shapes to facilitate:
  - Meaningful quantitative analysis of spatial gene expression patterns
  - Learning the underlying model of the imaginal disc shapes for use with model based techniques





 A set of imaginal disc images of a specific class, with various stain patterns

- Known class labels
- Underlying shape model is unknown
- Transformation parameters unknown





- A clean shape model of the tissue class is generally not available
- Manually selecting features on images is expensive and time consuming
- Images have a lot of clutter and noise

#### Revisit: Can you see the difficulties?



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- Analysis of precise spatial gene expression patterns in <u>Drosophila</u> <u>embryos</u> through in situ hybridization[Berman et.al 2002, Tomancak et.al 2002]
  - Curation is manual
  - Requires annotation
- Automated <u>embryo</u> registration and stain classification [Peng and Myers (RECOMB 2004)] using Gaussian mixture models
  - Registration is very simplistic (major/minor axes)
- Shape learning and alignment is a well-studied problem
  - Miller et.al (CVPR 2000)
  - Charpiat et.al (ICIP2003)
  - Frey and Jojic (CVPR1999)
  - Tsai et.al(TMI 2003)

#### Data Flow in the Proposed Approach



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### Highlights of the Approach



- Proposed approach makes no assumptions on the underlying anatomy or shape
  - Generalizable to other gene expression studies
- Removes the need for experts to mark points of interest
  - Amenable to large scale automation
  - Unsupervised
  - Registration performance improves asymptotically as number of samples (images) increases
- Learned transformations are semantically meaningful
- Augments model based registration techniques
  - Learned model can be used to bootstrap model based methods
- Extendable to 3D datasets and gray-scaled valued datasets





- Manually segment a few sample images
  - Learn shape model from these images
- Combine variance segmented images with learned shape model to automate segmentation process



#### Joint Nonparametric Alignment and Shape Learning

- A LEASE AND A LEAS
- Learn MAP estimate of the underlying shape model
- Entropy minimization algorithm: Congealing (ref: Miller et. al. – CVPR '00)
  - Coordinate descent method
  - Input: A set of binary shape masks of tissues of a given class
  - Output upon convergence: Aligned binary shapes + corresponding transformations
    - Over parameterization used: x-translation, y-translation, rotation, x-log-scale, y-log-scale, x-shear, y-shear

#### Mean Images from Shape Learning Stage





Wing, Haltere, Leg, Eye discs

A: Before Alignment; B: Alignment with 3 parameters;

C: Alignment with 7 parameters

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#### Alignment Results



Wing, Leg, Eye discs: A: Before Alignment; B: Alignment with 3 parameters; C: Alignment with 7 parameters

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#### Stain Scored Patterns: Aligned Vs. Unaligned





Wing discs: A: Before Alignment; B: After Alignment with 7 parameters





#### For Further Details:

- Parvez Ahammad, Cyrus Harmon, Ann Hammonds, Shankar Sastry and Gerald Rubin, 'Joint Nonparametric Alignment for Analyzing Spatial Gene Expression Patterns of Drosophila Imaginal Discs', Proceedings IEEE Conference on Computer Vision and Pattern Recognition, June 20-25, 2005, San Diego, CA, USA.
- Erik Miller, Nick Matsakis and Paul Viola, 'Learning from One Example Through Shared Densities on Transforms', Proceedings IEEE Conference on Computer Vision and Pattern Recognition, Vol. 1, pp. 464-471, 2000.



# Thank you!

# Questions?