Robust Region Landmark Detection for Mouse Brainstem Section Images

Yuncong Chen and Yoav Freund

Department of Computer Science and Engineering,
University of California, San Diego, La Jolla, CA 92122, USA

Abstract. **Keywords:** landmark detection, atlas generation, mouse brain, gabor filter

1 Introduction

Registering brainstem is hard due to the lack of sharp edges, compared to Cerebral Cortex and Cerebellum.

Allen Reference Atlas does not have enough details in brainstem.

2 Related Work

Point Landmark Detection
  SIFT
Saliency and Objectness Detection
  global rarity scheme
  center-surround scheme
Texture Representation
  gabor filter
  textons

3 Representing Texture using Histograms of Gabor Textons

Represent texture at each pixel using Gabor filters.

rotation-invariant k-means clustering to form textons.

Over-segment into superpixels.

Describe texture using histogram of textons

4 Detecting Significant Region Using Center-Surround Contrast

Grow each superpixel into a region.

Score is computed as the center-surround contrast of the texton histograms.

5 Detecting Boundaries by Region Concensus

Instead of voting for each superpixels as boundary separately, vote for them as a set.

Each growed region vote according to their saliency scores.

Each boundary is described by a tuple that consists of four elements:

1. x-y positions of every superpixel on the boundary
2. centroid of the expansion cluster inside the boundary
3. the average texton distribution of interior superpixels
4. a list of texton distributions of exterior superpixels (more precisely, the closest layer of superpixels on the outside of the boundary).

6 Matching Boundaries from Different Sections

distance = interior + exterior + shape + location

Distance between boundaries are defined as a weighted combination of:

1. Jenson-Shannon divergence between interior distributions
2. symmetric Hausdorff distances between the two sets of exterior distributions. That is, the maximum among the distances between each distribution and its closest distribution from the other set. Here the distance is the Jenson-Shannon divergence.
3. shape dissimilarity: total chi2-distances of shape context descriptors after correspondences are identified for superpixels on two boundaries using dynamic programming. (This is essentially the Shape Distance in Section 5.1 of Belongie's paper)
4. spatial distance: Euclidean distance between cluster centroids

Boundaries are detected from two sections and their pairwise distances are computed. A pair of boundaries are matched if they are the closest boundary of each other.

7 Experiments

7.1 comparison with human labelings

Shows the results of our algorithm is comparable to human labeling.

show results for RS141. (Do we need to do more than one stacks here? I think one stack already shows enough variations. A coronal stack would be good, but we don't have any now).

7.2 robustness of matching

Shows that matchings are robust to distortion and shape change. Also shows that our distance measure is a sensible one: each of the four terms is important. We show this by changing the term weightings, and then compare matching results.

8 Future Work

use detected landmarks for registration
learn visual words using deep neural networks

References

1. Clarke, F., Ekeland, I.: Nonlinear oscillations and boundary-value problems for Hamiltonian systems. Arch. Rat. Mech. Anal. 78, 315–333 (1982)