Scalable Alignment of Electron Microscope Image Sections

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Overview

- **Goals**
  - Scalable alignment of 3D Electron Microscope sections of mouse brain.
  - Integration with CAJAL-3D API for easy image retrieval and upload from database.
- **Difficulties**
  - Approach must be scalable.
  - ($1024 \times 1024 \times 2000$ in the smallest data set $\approx 2B$ voxels.)
  - Most datasets occupy TB of space; infeasible do align all at once.
- **General Method**
  1. Compute the transformations for alignment between adjacent pairs of images using cross-correlation.
  2. Globally align an entire image cube using pairwise transformation parameters.

Pairwise Alignment

Objective: Compute the transformations necessary to align adjacent pairs of images.

Outline of procedure:

1. Compute pairwise transformation parameters.
2. Improve rotation parameter through error minimization.
3. Refine transformations using image data outside pairwise images to minimize error.

Objective: Determine the transformations necessary to align image pair.

For each pair of images:

1. Apply median filtering, histogram equalization, and hamming window.
2. Take Discrete Fourier Transform, apply high-pass filter, and resample in log-polar coordinates.
3. Find best ρ, θ by correlation and max picking.
4. Rotate image, then correlate to find the best translation parameters.
5. Use Support Vector Machine (SVM) to identify peak in cross-correlation of image pair.
6. Save the transformation parameters.

Pairwise Alignment

Peak Identification

Objective: Determine peaks in the cross-correlation of two images that correspond to translations for correct alignment.

- Support Vector Machine (SVM)
  1. Train SVM classifier with selected peak features from already aligned images (ground truth).
  2. Partition cross-correlation of pairwise images into 9 equal parts.
  3. Find the coordinate of maximum intensity point in each partition.
  4. Sort the coordinates with respect to maximum intensity.
  5. Classify each of the 9 potential peaks in descending order until a peak is found.
  6. If none of the peaks are classified as peaks, then no peaks detected.
- Other Attempted Methods:
  - Choose maximum values.
  - Correlate pairwise cross-correlation with normal distribution.

Pairwise Alignment

Improve Rotation Parameter

Objective: Evaluate the correct alignment rotation with a finer level of discretization.

1. Given initial estimate of rotation angle θ necessary to align images...
2. Iterate for each k over a small window $\theta_{new} = [\theta - k\epsilon, \theta + k\epsilon]$, in increments of ϵ.
3. Compute alignment error with θ_{new} as rotation angle.
4. Update rotation parameter with angle that minimizes Mean Squared Error (MSE) between image pair.

Objective: For alignment of image pair I_2, I_3, use data from images I_1 and I_4.

1. Calculate pairwise transformation parameters between I_1, I_3 and I_2, I_4.
2. Obtain 2 more estimations of transformation parameters between I_2, I_3 using new information.
3. Determine the Mean Squared Error between image pair using all estimates of transformations.
4. Pick transformation that minimizes error.

Global Stack Alignment

Objective: Given transformation parameters between all adjacent image pairs, compute transformation to each image in global coordinate frame.

1. Set global transformation parameters of previous image to that of current image.
2. Find new rotation angle by adding previous rotation parameter to pairwise rotation angle.
3. Find new translation parameters using previous rotation angle and pairwise translations.
4. Positive translations: shift current image. Negative translations: shift all previous images.
5. Iterate through image cube to globally align stack.

Other Attempted Methods

- RANSAC to detect linear folds
- SURF feature matching to align images
- Superpixels and Earth Mover's Distance as a better error metric for image alignment

References

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