A Two-Stage Minimum Spanning Tree (MST) based Clustering Algorithm for 2D Deformable Registration of Time Sequenced Images

by

Baidya Nath Saha[1], Nilanjan Ray[2], Sara McArdle[3], and Klaus Ley[4]

[1]Centro de Investigación en Matemáticas (CIMAT), Monterrey, México
[2]Department of Computing Science, University of Alberta, Canada,
[3,4]La Jolla Institute for Allergy & Immunology, La Jolla, CA, USA
[1]baidya.saha@cimat.mx, [2]nray1@ualberta.ca,
{[3]smcardle, [4]klaus}@liai.org

Outlook of the Presentation

- Introduction
- Minimum Spanning Tree (MST) based Clustering Algorithm
  - MST based graph construction
  - Graph clustering
  - Anchor selection and image registration
- Efficacy of Proposed Algorithm
- Experimental Results and Discussions
- Conclusions and Future Works

Introduction

- Significant cardiac and respiratory motion of the living subject, occasional spells of defocus, drifts in the field of view, and long image sequences make the registration of *in-vivo* microscopy image sequences used in atherosclerosis study an onerous task.

- In this study, we develop and implement an optimal sequence optimization algorithm for long microscopy image sequence registration.

- We first reorder the natural temporal image sequence using minimum weighted spanning tree (MST).

- In this study, we developed and implemented a novel Minimum Spanning Tree (MST) clustering based 2D deformable image registration method for noisy long time-sequenced images where poor quality images lie in between the sequences.

Minimum Spanning Tree (MST) based Clustering Method

MST based Clustering Algorithm consists of three sequential steps:

1. **MST based Graph Construction**

- Construct a graph for the input image sequence.

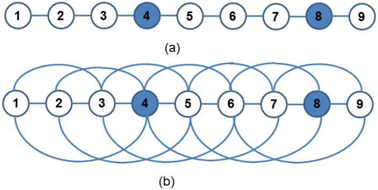


Figure: (a) A time-sequenced set of nine images. Shaded circles represent poor quality images. (b) A graph constructed on the image sequence.

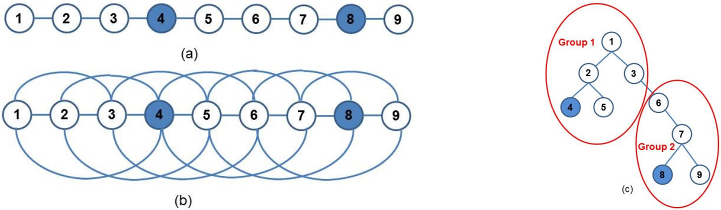
Minimum Spanning Tree (MST) based Clustering Method

❶ MST based Graph Construction

- Then construct a MST. The edge weights are constructed as follows:

$$E(I_i, I_j) = \begin{cases} ||I_i - R(I_i, I_j)|| & \text{if } i \neq j \text{ and } |i - j| \leq \delta \\ \infty, & \text{otherwise,} \end{cases}$$

- $R(X, Y)$ denotes the registered source image Y *w.r.t.* the target image X.
- δ controls the sparsity of the graph. A smaller value of δ illustrates greater sparsity. For a complete graph, $\delta = n - 1$. The computational complexity of MST-based registration is $O(\delta n)$, while the computational complexity of adaptive template matching is $O(n)$.



Minimum Spanning Tree (MST) based Clustering Method

❷ Graph Clustering

- Cluster MST into M groups as demonstrated in Fig.(c).
- Users can select the value of M or the value of M can be chosen automatically.

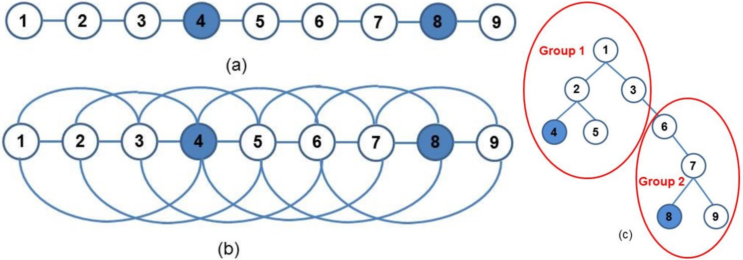


Figure: (a) A time-sequenced set of nine images. Shaded circles represent poor quality images. (b) A graph constructed on the image sequence. (c) An example of clustering minimum weighted spanning tree.

Minimum Spanning Tree (MST) based Clustering Method

❸ **Anchor Selection**

- Most of the available methods pick either first or middle image of the sequence as the anchor image.
- In this study, we develop an optimal anchor image selection algorithm through an iterative assessment of image entropy and Mean Square Error (MSE) during the registration process.
- Structural similarity measure is widely used for registration purposes. However, due to distortions, structural similarity cannot always be maintained even for consecutive slices.
- MSE performs poorly to measure image distortion for long time sequenced slices since a subsequence (normally initial and end slices) contain little information due to the topology of the animal organs.
- Hence, we incorporate entropy along with MSE for anchor selection.

Proposed MST based 2D Clustering Algorithm

Algorithm 1 MST based 2D deformable registration algorithm

Run the MST algorithm to reorder the image sequence so that poor quality images lie at the end of the sequence.
Cluster the MST into M groups, $\mathbf{G_1}$, ..., $\mathbf{G_M}$ using normalized graph cut.
for $k = 1, ..., M$ **do**
    Find the anchor image AI_k for each group G_k using algorithm 2.
    Perform **deformable** registration of images in group k with respect to the Anchor Image AI_k.
end for
Set the number of groups to one, obtain the final Anchor Image AI_{final} using algorithm 2.
Align each image of the sequence to the target AI_{final} using **deformable** registration.

Anchor Selection

Algorithm 2 Automatic anchor selection from a set of images

1: Compute the feature (say entropy) for each image of the set of images S , $h(I_u), I_u \in S$.

2: Select the anchor from a set of images S having the highest entropies $j_k = argmax_{u \in S}\{h(I_u)\}$.

3: Align each image $\{i | i \neq j_k\}$ of the set S into Anchor j_k according to MST traversal order using rigid registration and compute MSE_{i,j_k} for the set S.

4: Find the image having minimum MSE_{i,j_k} of set S, $j^* = argmin_{i \neq j_k \in S}(MSE_{i,j_k})$.

5: Align anchor I_{j_k} into image I_{j_*} using rigid registration and compute the registration error MSE_{j_k,j_*}.

6: Replace Anchor I_{j_k} by I_{j_*} if $MSE_{j_k,j_*} < MSE_{j_*,j_k}$.

Efficacy of Proposed Algorithm

❶ *Mitigate the registration error propagation.*

- For a longer sequence, normally the topology of the anchor image is quite different from many images located far away from it due to larger drift and change of illumination available in atherosclerosis dataset.
- Proposed MST based registration algorithm minimizes the registration error propagation by decomposing the original image sequence into smaller sub-sequences in such a way that these smaller sub-sequences contain poor quality images toward their end.

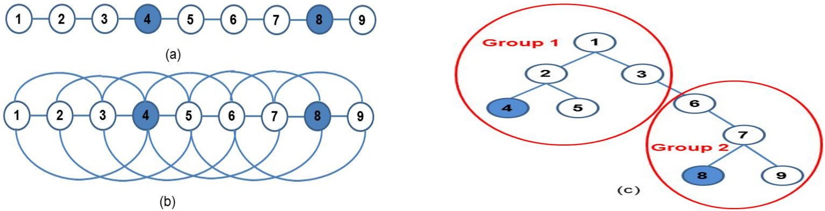


Figure: (a) A time-sequenced set of nine images. Shaded circles represent poor quality images. (b) A graph constructed on the image sequence. (c) An example of clustering minimum weighted spanning tree.

Efficacy of Proposed Algorithm

❷ *Incorporate larger drift.*

- In two-stage registration, first images are registered with the local anchor, the topology of which is closer to the candidate images than the global anchor image. Then images are registered with global anchor image.

- Incremental adjustment of the two-stage deformable registration can accommodate large distortion of the structures and artifacts better than single stage deformable registration.

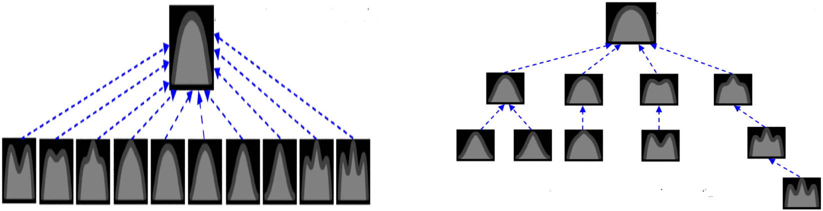


Figure: Left: Normal Registration and Right: MST based Registration.

Efficacy of Proposed Algorithm

- Simple template matching method lies into one extreme in that it subdivides the input sequence into the largest number sub-sequences and prevents the error propagation due to poor quality images.
  - Since the sequences are long, the anchor image in simple template matching cannot adapt to the illumination changes and drifts.

- The sequential methods, such as StackReg, lies on the other extreme end in that it divides the input sequence into at most two sub-sequences.
  - So, they can handle the drift and change of illumination; however, they fail to tackle occurrences of poor quality images.

- MST based graph clustering algorithm decomposes the original image sequence into smaller sub-sequences and these smaller sub-sequences contain poor quality images toward their end.
  - Thus, registration error propagation is minimized. Our MST based graph clustering algorithm achieves a balance between these two extremities.

Experimental Results and Discussions

- We conducted experiment on *in-vivo* microscopy image sequences of mouse arteries dedicated for atherosclerosis study.
- The datasets pose several technical challenges to image sequence alignment such as:
  - These sequences are often long, exceeding 1000 images;
  - The motion artifacts are significant due to the cardiac and the respiratory motions;
  - There are occasional changes in focal plane and drifts in the field of view;

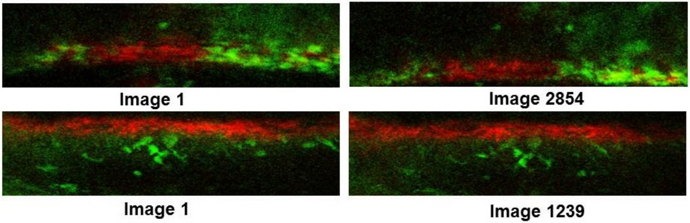


Figure: Two rows illustrate two different datasets. The first and the second columns show the first and the last images in the sequences.

Experimental Results and Discussions

- We used structural similarity index (SSIM), which is a popular quality metric to compare registration algorithms.
- The value of SSIM lies between -1 and 1. Higher SSIM values demonstrate better registration between two images.
- we used the optimal value of $\delta = 6$ for both MISTICA and our method.
- Number of clusters is chosen as 5 through cross validation.
- The registration function $R(X, Y)$ used translational motion.

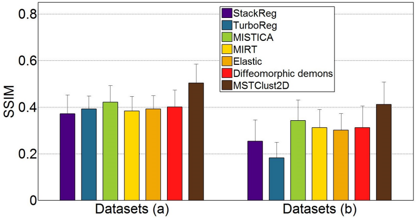


Figure: SSIM for different image registration methods on two different datasets.

Conclusions and Future Works

- We first offer a generalized framework for selecting optimal sequence for both 2D and 3D deformable registration from long time sequenced *in-vivo* microscopy image sequences.
- For a longer sequence, normally the topology of the anchor image is quite different from many images located far away from it due to larger drift and change of illumination available in atherosclerosis dataset.
- MST based graph clustering algorithm minimizes the registration error propagation by decomposing the original image sequence into smaller sub-sequences in such a way that these smaller sub-sequences contain poor quality images toward their end.
- In two-stage registration, first images are registered with the local anchor. Then images are registered with global anchor image.

Conclusions and Future Works

- Stage wise incremental adjustment can accommodate large distortion of the structures and artifacts better than standard deformable registration.
- In this research we develop a robust and automatic anchor image selection method through an iterative assessment of MSE and entropy and thus avoids the user interaction during the longer registration process.
- This algorithm has only two tuning parameters, graph width and number of clusters in the graph, making it more user friendly than many existing techniques.
- We would like to extend the proposed minimum spanning tree based graph clustering framework to temporal sequences of 3D volumes.

THANK YOU