MINIMUM SPANNING TREE FUSING MULTI-SALIENT POINTS HIERARCHICALLY FOR MULTI-MODALITY IMAGE REGISTRATION

Shaomin Zhang, Lijia Zhi, Dazhe Zhao and Hong Zhao
College of Information Science and Engineering, Northeastern University, Shenyang, Liaoning, China
Key Laboratory of Medical Image Computing (Northeastern University) Ministry of Education, China

Keywords: Medical Image Registration, Entropic Spanning Graph Estimator, Minimum Spanning Tree (Mst), Rényi Entropy, Salient Point.

Abstract: In this paper, we propose a novel registration algorithm based on minimal spanning tree. There are two novel aspects of the new method. First, instead of a single feature points, we extracted corner-like as well as edge-like points from image, and also added a few random points to cover the low contrast regions; Second, the hierarchical mechanism which fusing multi-salient points is used to drive the registration during the registration procedure. The new algorithm has solved the low robustness brought by the instability of extraction of feature points and the speed bottleneck problem when using MST to estimate the Rényi entropy. Experiment results show that on the simulated and real brain datasets, the algorithm achieves better robustness while maintaining good registration accuracy.

1 INTRODUCTION

Medical image registration is the basis of medical image fusion, and has been used in medical diagnosis, treatment, research, etc. Information-theoretic metrics, such as Shannon entropy, Rényi entropy, Tsallis entropy, etc, have been widely used in medical image registration. Information-theoretic metric are needed to estimate the entropy from the image data. Currently, there are three types of nonparametric entropy estimation methods: plug-in, sample-spacings and entropic spanning graphs estimator (Beirlant et al., 1997; Hero et al., 2002). Plug-in estimator is simple, and suitable for low dimensional space. But in high dimensional space, it will encounter "dimension disaster" problem. Sample-Spacings estimator was originally developed for one- dimensional samples. Miller (Miller, 2003) extended this technique to higher dimensions using Voronoi regions and Delaunay triangulations. Graph-based entropy estimators have faster asymptotic convergence rates, especially for non-smooth densities and for low dimensional feature spaces; they completely bypass the complication of choosing and fine tuning parameters; they can be easily extended to higher dimensional space (Hero et al., 2002). Redmond and Yukich (Redmond and Yukich, 1996) proved that when a graph is "quasi-additive" in d-dimensional feature space, d>=2, the graph can be used to estimate the entropy directly. Hero (Hero et al., 2002) pointed that among the currently known quasi-additive algorithms, the MST is the fastest (with polynomial run time) and applied it to image registration.

On this basis, scholars have done relevant research in the field of medical image registration (Sabuncu and Ramadge, 2004, 2008) and found that it will encounter speed bottleneck when using MST to estimate the entropy. In order to make constructing MST feasible for image registration problem, appropriate features must be extracted to compress the original great amount of data. Ma (Ma et al., 2000) registered two images using uniform sub-sampling. Sabuncu (Sabuncu and Ramadge, 2004) proposed two (deterministic and stochastic) non-uniform sub-sampling methods for improving the efficiency. But, uniform sub-sampling method treats each pixel equally during the registration procedure, regardless of whether some voxels are more important than others in registration. Gradient based sub-sampling method is sensitive to noise, and feature points are of poor stability.

Zhang S., zhi L., Zhao D. and Zhao H. (2010).
MINIMUM SPANNING TREE FUSING MULTI-SALIENT POINTS HIERARCHICALLY FOR MULTI-MODALITY IMAGE REGISTRATION.
In *Proceedings of the International Conference on Computer Vision Theory and Applications*, pages 33-36
DOI: 10.5220/0002820700330036

In this paper, we propose a novel hierarchical multi-modality registration algorithm which fusing multi-salient points based on minimal spanning tree. This new method not only considers multi- salient points, but also considers hierarchical mechanism during the registration procedure to improve the robustness of the registration. Experimental results showed that the new method has higher success rate than single feature and uniformly sub-sample methods based on minimum spanning tree on the images from BrainWeb (Collins et al., 1998) and Vanderbilt Retrospective Registration Project(RREP) (West et al., 1997).

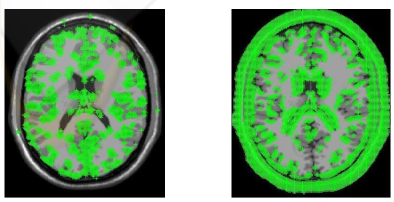
2 METHOD

2.1 Salient Point Extraction

Salient points contain structural and texture information, which is important for image registration. For example, the voxels that lie in the region of interest or at the boundary of region are more significant for image analysis. First, we removed the background of the image by the threshold of grey value. Second, similar to Harris detector and Yang's method (Harris and Stephens, 1988; Yang et al., 2007), we use auto-correlation matrix as a single response measure to produce potential corner like and edge like points. At each pixel location x, the Auto-correlation matrix, μ is computed,

$$\mu(x)=\begin{bmatrix}\mu_{11} & \mu_{12}\\ \mu_{21} & \mu_{22}\end{bmatrix}=g(\sigma)*\begin{bmatrix}L_x^2(x) & L_xL_y(x)\\ L_xL_y(x) & L_y^2(x)\end{bmatrix} \qquad (1)$$

Where g is a Gaussian function with standard deviation σ. L_α is the derivative computed in the α direction. $\lambda 1$ and $\lambda 2$ are the eigenvalues of μ. Potential corners are at pixels where $\lambda 1 / \lambda 2 > 0.1$. Potential edge points are at pixels for which $\lambda 1 / \lambda 2 <= 0.1$. Finally, we got the corner like points and the edge like points. The result is illustrated in Fig.1.



(a) Potential corner-like points (b) Potential edge-like points

Figure 1: Salient point extraction.

2.2 Hierarchical Registration Mechanism

In section 2.1, we have got potential corner and edge points. However, there are two problems in constructing MST. First, the sum of corner and edge points is so many, resulting in the speed bottleneck. Second, many low-contrast regions are not covered by any of salient points, resulting in much registration errors. So we use hierarchically mechanism, which was first proposed by Shen and Davatzikos (Shen and Davatzikos, 2002), to select salient points as the active points to drive the registration during the registration procedure. To make these points local adaptive, we divided the image into 10*10 sub-regions. In each sub-region, we sort the voxels by corner measure and edge measure respectively.

Corner measure: cornerness = det($\mu(x)$) – α trace^2($\mu(x)$);

Edge measure: edgeness = trace($\mu(x)$);

In order to make the distribution of the active points more uniform and the method more robustness, we add some random points to cover the low contrast regions. The hierarchical selection of active points in three registration phases is showed as follows:

- First phase: During the initial registration phase, in each sub-region, the highest strength point of the corner values is selected as active point. In this way, we can also select edge point. If the region doesn't have any active points, we will add two random points. If the region has only one active point, we will add one random point to the region.
- Second phase: With progress of registration, those second strength potential corner and edge points will be selected as active points to drive the image registration, leading to the refinement of registration results. If the region doesn't have enough active points, we will add random points as first phase.
- Third phase: Finally, those third strength corner and edge points will be considered as active points for image registration. If the region doesn't have enough active points, we will add random points as first phase.

In each registration phase, we will construct MST on the active points.

2.3 Entropic Spanning Graph Estimator

Given $V=\{P_i|P_i \in R^2,\ i=1,\ldots,n\}$ of n vertices, a spanning tree is a connected acyclic graph which passes through every vertex. All n vertices are connected by edges $E=\{e_{ij}=(P_i, P_j)|i, j=1,\ldots,n, i\neq j\}$. For a given edge weight exponent γ, the minimum spanning tree is the spanning tree which minimizes the total edge weight of the graph,

$$L(V)=\sum_{e_{ij}\in MST}|e_{ij}|^{\gamma} \tag{2}$$

For a continuous pdf f, Rényi entropy $H_\alpha(f)$ is defined as,

$$H_\alpha(f)=\frac{1}{1-\alpha}\log\int f^{\alpha}(x)dx \tag{3}$$

where $\alpha=(d-\gamma)/d$.

Steele (Steele, 1998) has proved that the length of the MST has the following asymptotic property,

$$\lim_{n\to\infty}\frac{L(V)}{n^{\alpha}}=\beta_{\gamma}\int f^{\alpha}(x)dx \tag{4}$$

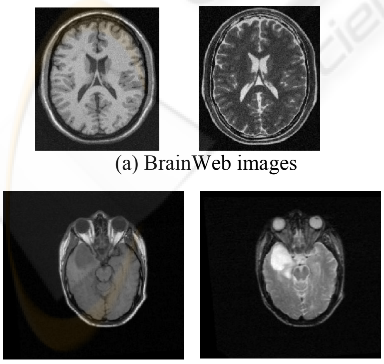
Where β is a constant independent of f.

Combining (3) and (4), we obtain an estimator of Rényi entropy from the total edge weight of the MST,

$$\begin{aligned}\hat{H}_\alpha(f)&=\frac{1}{1-\alpha}\left[\log\frac{L(V)}{n^{\alpha}}-\log\beta_{\gamma}\right]\\ \Rightarrow\quad \hat{H}_\alpha(f)&\propto\frac{1}{1-\alpha}\log\frac{L(V)}{n^{\alpha}}\end{aligned} \tag{5}$$

It follows directly from the results of Steele (Steele, 1998) that the MST estimate $\hat{H}_\alpha$ is a strongly consistent estimator of H_α.

3 EXPERIMENTAL RESULTS



(a) BrainWeb images

(b) RREP images

Figure 2: DataSets.

In this section, we present two sets of experiments. The first set of experiments is used to test several variations on the choice of salient points. The second set is used to evaluate the performance of proposed method, compared to traditional uniform sub-sampling based multi-resolution image registration. All experiments are tested on simulated and real 2D MR brain images.

Figure 2(a) are the T1 and T2 MR brain images with 5% noise and 20% intensity non- uniformity obtained from the BrainWeb MR. Figure 2(b) are the T1 and T2 MR brain images provided by RREP, first of all, we register the two images by using their fiducial markers, and then do the experiment.

3.1 Choice of Salient Points

T1 and T2 MR Brain images of the two datasets were used to evaluate variations on the choice of the salient points. T1 image is transformed by a angle randomly generated from the different range of degree, and two translations (T_x, T_y) from the different range of pixels. For simulated BrainWeb dataset, the range is [-15, 15] and [-20, 20], while for the real RREP dataset, the range is [-10, 10] and [-15, 15]. Each dataset generates 50 randomly transformed T1. Then the T2 image is registered to the transformed T1. The registration is regarded as success if the translation errors on both axes are below 2 pixel and rotation error below 2 degree. The success rates of all salient point- based registration methods were listed in table 1.

Table 1: Comparison of the choice of the salient points.

DataSet	Range	Success Rate (%)		
		Our	Corner-only	Edge-only
BrainWeb	[-15, 15]	98	88	82
	[-20, 20]	84	84	70
RREP	[-10, 10]	100	92	98
	[-15, 15]	72	68	68

From Table 1, we can conclude that this combination of multi-salient points performed better than both methods alone for two test datasets. Particular for BrainWeb image with 5% noise and 20% intensity non- uniformity dataset, the performance of the edge-based method is lower than our method due to the edge-base method is more sensitive to noise.

3.2 Comparison of Registration Methods

Similar to section 3.1, the success rates of our propose method and uniform sub-sampling based method was calculated and listed in Table 2. It is

Table 2: Comparison of registration methods.

DataSet	Range	Success Rate (%)	
		Our	Uniform sub-sampling
BrainWeb	[-15, 15]	98	96
	[-20, 20]	84	86
RREP	[-10, 10]	100	70
	[-15, 15]	72	58

Table 3: Comparison of means and standard deviations of registration errors.

DataSet	Range	Mean and Standard deviation					
		Our			Uniform sub-sampling based		
		Tx	Ty	Rz	Tx	Ty	Rz
BrainWeb	[-15, 15]	0.27±0.17	0.21±0.16	0.20±0.17	0.25±0.17	0.16±0.11	0.21±0.14
	[-20, 20]	0.21±0.14	0.19±0.15	0.20±0.14	0.27±0.17	0.16±0.14	0.23±0.17
RREP	[-10, 10]	0.66±0.43	0.58±0.43	0.66±0.32	1.03±0.56	0.59±0.43	0.51±0.45
	[-15, 15]	0.93±0.57	0.79±0.58	0.69±0.34	0.93±0.54	0.58±0.49	0.47±0.36

clearly that the proposed method outperformed traditional uniform sub-sampling based method.

For those successful cases of registration, mean and standard deviations of rotation errors and translation errors were calculated and summarized in Table 3. We can observe that the accuracy of our proposed method is comparable to that of uniform sub-sampling based method.

4 CONCLUSIONS

In this paper, we have presented a novel method of constructing minimal spanning tree for multi-modality image registration. The new method hierarchically fuses multi-salient points to construct MST. This new method integrates not only more information obtained from multi-salient points to improve robustness of image registration, but also hierarchical mechanism to produce relatively accurate registration results. Experiment results show that on the simulated and real brain datasets, the algorithm achieves better robustness while maintaining good registration accuracy.

REFERENCES

Beirlant, J., Dudewicz, E. J., Gyorfi, L., and van der Meulen, E.C. (1997). Nonparametric entropy estimation: An overview. *International Journal of Mathematical and Statistical Sciences*, 6(1):17–39.

Collins,D.L., Zijdenbos,A.P., Kollokian,V., Sled, J.G., Kabani, N.L., Holmes, C.J., and Evans, A.C. (1998). Design and construction of a realistic digital brain phantom. *IEEE Trans. Med. Imag.*, 17:463-468.

Harris, C., Stephens, M. (1988). A Combined Corner and Edge Detector. In *Alvey Vision Conference,* pages 147-151.

Hero, A., Ma, B., Michel, O., and Gorman, J. (2002). Applications of entropic spanning graphs. *IEEE Signal Processing Magazine*, 19(5):85–95.

Ma, B., Hero, A., Gorman, J., and Michel, O. (2000). Image registration with minimal spanning tree algorithm. In *ICIP*.

Miller, E. (2003). A new class of entropy estimators for mult-dimensional densities. In *Proc. ICASSP*.

Redmond, C., Yukich, J. (1996). Asymptotics for Euclidean functionals with power weighted edges. *Stochastic Processes and their Applications*, 61(2):289-304.

Sabuncu, M. R., Ramadge, P.J. (2004). Gradient based nonuniform subsampling for information-theoretic alignment methods. In *EMBC.*

Sabuncu, M. R., Ramadge, P. J. (2008). Using Spanning Graphs for Efficient Image Registration. *IEEE Transactions on Image Processing*, 17(5):788-797.

Shen, D., Davatzikos, C. (2002). HAMMER: hierarchical attribute matching mechanism for elastic registration. *IEEE Trans. Med. Imaging*, 21(11): 1421–1439.

Steele, J. M. (1988). Growth rate of Euclidean minimal spanning trees with power weighted edges. *Ann. Probab.*, pages 1767–1787.

West, J., Fitzpatrick, J.M., Wang, M.Y., Dawant, B.M., Maurer Jr., C.R., Kessler, R.M., Maciunas, R.J., Barillot, C., Lemoine, D., Collignon, A., Maes, F., Suetens, P., Vandermeulen, D., van den Elsen, P.A., Napel, S., Sumanaweera, T.S., Harkness, B., Hemler, P.F., Hill, D.L.G., Hawkes, D.J., Studholme, C., Maintz, J.B., Viergever, M.A., Malandain, G., and Woods, R.P. (1997). Comparison and evaluation of retrospective intermodality brain image registration techniques. *J. Comput. Assist. Tomogr*, (4):554–566.

Yang, G., Stewart, C., Sofka, M., Tsai C. (2007). Registration of challenging image pairs: initialization, estimation, and decision. *IEEE Trans. Pattern Anal. Mach. Intell.*, 29(11):1973-1989.