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A novel label fusion technique for segmenting subcortical brain structures using multi-atlas and multi-graphcuts

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Abstract

Image segmentation plays most important role in computer vision. Segmentation of medical image is the first step in the diagnosis and treatment of various diseases. Segmenting brain MRI data is the most crucial step in medical image analysis. Template based segmentation gives good results when compared to other segmentation techniques. Using multiple atlases as templates, these methods, has two phases, registration and fusion. Registration is finding geometric relationship between two images, which yields segmentation for each atlas. After registration, label fusion step is required to fuse all segmentations into a single final segmentation. In this paper we propose a new label fusion strategy for segmenting sub cortical brain structures from T1 weighted MRI scans using priori knowledge and maximum multi graph cut. We test our framework for segmenting subcortical brain structures on the SATA(MICCAI 2012) challenge data set. We evaluate our algorithm using dice overlap and Jaccard similarity index.

Keywords: Multi atlas segmentation, Brain MRI, Subcortical brain structures, Multiway Patch MAXCUT (MP-MAXCUT)

Introduction

Automatic labeling of voxels in a MRI is a key step in the diagnosis of the disease. Since manual labeling is a time consuming one, automatic and semi-automatic labeling methods are proposed. Various algorithms such as SVM and artificial neural networks[1,2], appearance and shape-based algorithms[3], registration based approaches and deformation maps[4] have been proposed. Segmentation of anatomical brain structures using multi-atlas segmentation proved to be a successful one in the field of medical image analysis[5–9]. Using multiple atlases reduces the registration errors and improves segmentation performance if there are large structural variations. When multiple atlases are used, two steps are needed for segmentation: Registration of target image with each atlas image and fusion of all segmented images as a final segmentation. In registration step, a correspondence between target image and each atlas image is determined and labels from the atlas images are propagated into the target image. This method gives a set of segmentation which is then fused in the label fusion step. Graph based segmentation is the new segmentation method. Graph based segmentation methods are classified in two categories: deterministic and probabilistic[10]. Max-flow/min-cut and normalized cut algorithms belongs to deterministic method where are Bayesian network and MRF algorithms belongs to probabilistic method. In this paper, we proposed a novel method to fuse a set of segmented images into single images and segment the brain structures from T1 weighted MRI data using multiple atlases and using graph cuts. Image segmentation problem can be modeled as an energy minimization problem. Various energy minimization algorithms such as iterated conditional modes, graph cuts, tree-reweighted message passing and loop belief propagation are used in computer vision problems. Graph based energy minimization techniques have been successfully applied in solving computer vision problems. The advantage of using graph cut method is that it uses both regional and boundary information, also it globally optimize the energy minimization functions. In graph based method, usually, a fully connected graph is formed with the voxels of the image as vertices and edge weight is computed using the similarity between two vertices. Intensity is used for calculating the similarity between voxels. A graph min-cut method for segmentation is proposed by Boykovet. al.[11] and Kang et. al.,[12]. Slabaugh and Unal[13] use a shape prior term to the edges cost function. A Laplacian pyramid is used by Sinop and Grady[14] to reduce memory. To improve segmentation accuracy a graph cut active contours is proposed by Ning et al. [15].

Graph Cuts in labeling

Let G = (V, E) is a directed graph whose edge weights are non-negative and has two terminal vertices called s(source) and t(sink). An s-t cut called as graph cut is a partition of V into two disjoint sets VS and VT such that s ∈ VS and t ∈ VT. Every edge in the graph is assigned a cost. The minimum cut is the total cost of the edges that cuts the graph so that the source, S is completely separated from the sink T. Every edge in the graph will be assigned a cost. Usually there are two kinds of links, t-links and n-links. N-links represents the connection between two pair of neighbouring voxels. N-links are bi-directional whereas t-links are uni-directional. One of the most popular algorithms to solve max-flow/min-cut is Ford-Fulkerson algorithm. Other algorithms are Push-Relabel Algorithm, New Algorithm by Boykov, etc.

To define energy functions, two models can be used. They are Potts Interaction Energy Model and Linear Interaction Energy Model[16]

$$E(I) = \sum_{p\in P} |I_p - I_p^{\circ}| + \sum_{(p,q)\in \aleph} K_{(p,q)} . T(I_p \neq I_p) \quad [1]$$

Where I={Ip|p∈P} are unknown labels, I^o={I^op|p∈P} are known labels, K(p,q) is the Potts interaction which indicates the label discontinuities between adjacent pixels and T(.) is an indicator function.

$$E(I) = \sum_{p\in P} |I_p - I_p^{\circ}| + \sum_{(p,q)\in \aleph} A_{(p,q)} . T(I_p \neq I_p) \quad [2]$$

Where A(p,q) gives the interaction between the neighbouring pixels p and q.

Potts model is useful when the labels are piecewise constant and with discontinuities at boundaries whereas linear interaction model is useful when the labels are piecewise smooth and with discontinuities across the boundaries.

Greig et al. [17] were first to use the min-cut/max flow algorithms to minimize some energies and can be represented as w.

$$E(L) = \sum_{p\in P} D_p(L_p) + \sum_{(p,q)\in \aleph} V_{p,q}(L_p, L_q) \quad [3]$$

where L represents the label set, Dp represents data penalty function – cost of t-links, Vp,q represent interaction potential – cost of n-links, and N is a set of all pairs of neighbouring voxels. The first term represents regional term and the second term represents boundary term. They proved that an Ising model is used to define two label pairwise MRF, then the solution can be obtained using st min-cut problem.

Minimum cut produces bias in the clusters[18,19]. So a normalized cut was proposed by Shi and Malik [20] which used both group similarity and cluster dissimilarity.

$$Ncut(A,B) = \frac{cut(A,B)}{assoc(A,V)} + \frac{cut(A,B)}{assoc(B,V)} \quad [4]$$

Where assoc(A,V) is the weight of all edges from nodes in A to all the nodes in the graph. Normalized cut uses Eigen vectors of affinity matrices.

The weighting functions initially proposed in [21] but subsequently utilized throughout the segmentation literature are

Gaussian : wij=1/dist(vi,vj) exp(-β(g(vi)-g(vj))2) [5]

Reciprocal : wij=(1/dist(vi,vj)). (1/1+ β(g(vi)-g(vj))2) [6]

Where g(vi) indicates the image intensity at voxel viand β represents a free parameter. The function dist(·) accounts for differences in spacing and edge length and is computed as the Euclidean distance between voxels, taking into account voxel spacing.

Multiway Patch MAXCUT (MP-MAXCUT)

First we have to transform our problem into a graph and then we have to cut that graph into multiple parts. In our method we use maximum cut instead of min cut or normalized cut to segment the structures. In min cut methods, the edge weights is denoted by the distances based on intensity similarity between nodes[22] where as in our method also we use similarity between two nodes to represent the edge weights. But in our problem we do maximum cut instead of minimum cut. The drawback of the minimum cut method is that it favors cutting small regions of isolated nodes and hence to get a balanced segmentation we have to normalize the images. Normalized cut needs to compute Eigen vectors To overcome this drawback, we use maximum cut method. Our method use similarity between voxels as edge weights and hence we perform maximum cut. Maximum cut is a NP-complete problem. So we are use an approximation algorithm. A 4-neighbours graph is formed for each atlas image. The numbers of edges are reduced and this graph is a planar graph. Edge weights are assigned using the spatial proximity between two nodes which are measured using normalized correlation co-efficient. We perform max cut using dual scaling algorithm.

In our problem, there are as many terminal nodes as the distinct number of structures. We represent one terminal node for every structure. ie. one terminal node for each label. In our problem we use the similarity between two patches (target and atlas) as n-links edge cost. T-links represents the connection between the terminal nodes (labels) and patches. In our problem we use normalized correlation between the target image patch and the atlas image patch and assign this as t-links edge cost. Since normalized correlation coefficient is easy and fast to compute and does not affect by the intensity changes, it is suitable for patch based comparison of image blocks.

$$NC(TP1, A1P1) = \frac{\sum d(TP1(d) - \overline{TP1})(A1P1(d) - \overline{A1P1})}{\sigma_1 \sigma_2} \quad [7]$$

Where $\overline{TP1}$ and $\overline{A1P1}$ are mean of the target and an atlas patch, σ1 & σ2 are corresponding standard deviation.

Divide the target image into N patches and represent them as vertices of graph. Each node in the graph represents each voxel in the target image. Determine the distinct labels from the atlas images and draw terminal nodes for them. N-link weights represent the similarities between neighbourhood patches. Use normalized correlation co-efficient to measure similarities between two neighbouring patches. For each patch and for each atlas determine the corresponding patch label. Draw T-links between corresponding terminal (label) node and patch node and use normalized cross correlation between target and atlas patch to determine T-link weights. If there exists a T-link already, then update the weight and change the edge as super edge. Repeat this procedure for each target image patch and for each atlas. Perform maximum cut for each terminal node to partition the graph. Assign the label from the terminal node to all the vertices of the partitions. Figure 1 shows the graph for an image with 12 patches and 4 distinct labels. We elude some of the links for clarity.

The weights are high for two similar patches and low for dissimilar patches. Weights for n-links, WPij are determined using[13]

$$WPij = e^{\left(-\frac{d(i,j)}{\sigma R}\right)} e^{\left(-(\|WP(i)-WP(j)\|^2)/\sigma W\right.} \quad [8]$$

$$WP_i^{lj} = \frac{p(WPi|i\in lj)}{p(WPi|i\in lj)+p(WPi|i\in lj)} \quad [9]$$

where ||.|| denotes L2 norm. d(i,j) is the distance between the patches I and j. σR and σW are tuning parameters.

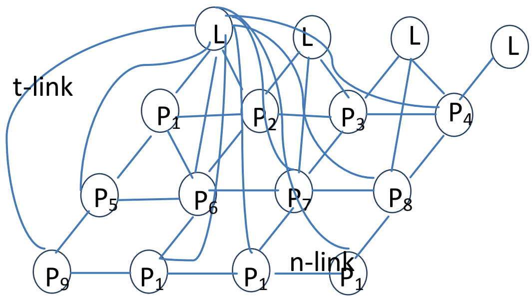

Figure 1. Graph for a target image with 12 patches and with 4 distinct labels from the atlases

Psuedo code for our algorithm is given below:
Graph *g;
For all distinct labels
Add terminal nodes
For each patch p in target image
Add a node to the graph
Add n-link between adjacent nodes
For each node in the graph,
Add t-link between node and each terminal node & Calculate t-link
weight using NCC between corresponding node and terminal node
and set Super edge & update weight if there exisits link
Update n-link weight using NCC between neigbouring nodes
end
g->compute_maxcut();
Assign labels for each voxels using the labels of the connected terminal node

Experiments and Results

We test our algorithm with the data set provided in MICCAI 2012 grand challenge. Leave-one-out cross validation tests is performed by comparing volumetric overlap with the pre-labeled training images. All implementations are done using C++ and ITK[23]. We first pre-process all the MRI images (bias correction, skull stripping and registration). We use ANTs N4 bias correction algorithm described by Tustison et. al. [24] for bias correction. After bias correction, all images (both test and atlases) are rigidly aligned with MNI template space using 3D Slicer's BrainsFit [25] for further processing. For removing non-brain tissues, we use ROBEX[26] skull stripping algorithm proposed by Iglesias et. al.[27]. Top 10 atlases are selected from the atlas set by calculating similarity, using mutual information between the test image and each atlas. For evaluation purpose we segment three structures, Amygdala, Basal Ganglia and Hippocampus for all the 15 training data set from MICCAI 2012 grand challenge data set. We select these three structures since these structures are challenging to segment because of large variations. For comparison we use Jaccard co-efficient, Dice similarity, false negative and false positive[28]. The results for segmenting a single scan is compared with its golden standard and summarized in the table 1 and figure 2 shows the plot for the same.

Table 1 Performance comparison of segmentation of three structures

Structures	Amygdala	Basal Ganglia	Hippocampus
Target Union	0.7	0.918367	0.675497
Jaccard	0.59882	0.538043	0.511377
Mean (dice)	0.749077	0.699647	0.676703
False negative	0.3	0.0816327	0.324503
False positive	0.194444	0.434932	0.322086

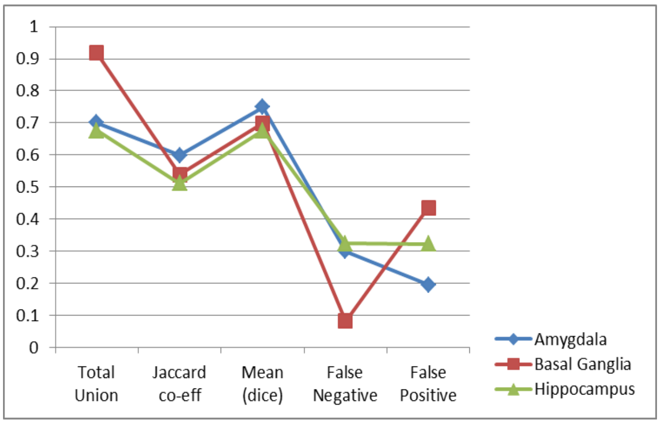

Figure 2 Plot for comparison of segmentation of three structures

The evaluative results for dice similarity, jaccard co-efficient, volume similarity, false negative and false positive are given in table 2 and figure 3. For performance evaluation of our method, test results for simple majority voting and minimum multiway cut is also given.

Table 2 Performance comparison of segmentation of our algorithm, simple majority voting and min multiwaycut

	MP-MAX CUT	Simple Majority Voting	Minimum Multiway cut
Total Union	0.777384	0.678554	0.547851
(jaccard)	0.660977	0.56743	0.423401
Mean (dice)	0.79589	0.543456	0.445321
Volume sim.	0.04761	0.14356	0.215321
False negative	0.222616	0.456781	0.532511
False positive	0.184702	0.562312	0.5938531

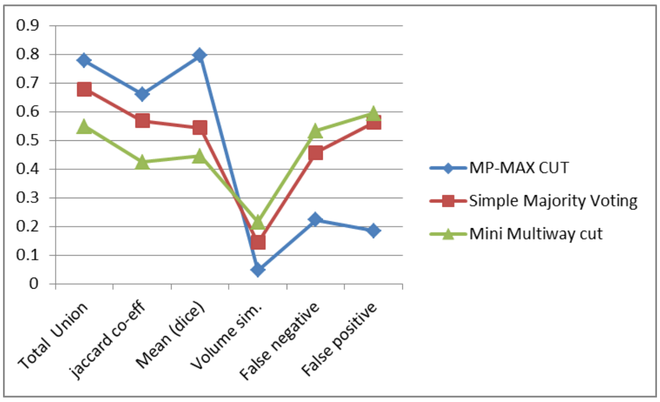

Figure 3 Plot for the performance comparison of segmentation of our algorithm, simple majority voting and min-multiwaycut

Conclusion

In this paper, we have proposed a technique for segmenting sub cortical brain structures of MRI of human. We use both the spatial correspondences and intensity similarity in the label fusion step. A new label fusion technique using maximum multiway graph cut is proposed. By measuring the patch similarities between two neighbourhood patches and between target and atlas image patches, as edge weights, we use a max graph cut to assign a label to each voxels. We test our algorithm in the public data set and our algorithm produces good segmentation when compared with simple majority voting and minimum multiway cut algorithms. The future extension involves executing the same algorithms for noisy images as well as to decrease the time taken for segmentation. Also by applying various sparsification techniques we will try to reduce the computational complexity and dimensionality of the graph.

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