Knowledge-Based Segmentation of Brain MRI Scans Using the Insight Toolkit

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Abstract. An Insight Toolkit (ITK) implementation of our knowledge-based segmentation algorithm applied to brain MRI scans is presented in this paper. Our algorithm is a refinement of the work of Teo, Saprio, and Wandall. The basic idea is to incorporate prior knowledge into the segmentation through Bayes' rule. Image noise is removed via an affine invariant anisotropic smoothing of the posteriors as in Haker et. al.
We present the results of this code on two different projects. First, we show the effect of applying this code to skull-removed brain MRI scans. Second, we show the effect of applying this code to the extraction of the DLPFC from a user-defined subregion of brain MRI data. We present our results on brain MRI scans, comparing the results of the knowledge-based segmentation to manual segmentations on datasets of schizophrenic patients.

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This paper provides details about the inclusion of our knowledge-based segmentation algorithm into ITK. In section 2, we provide a high-level overview of our algorithm. Since this is an ongoing project that will experience future paper and code revisions, we include in section 3 the current project status. In section 4, we give an explanation of the filter from the user's point of view. In section 5, we discuss the role of open source development in this project. In section 6, we share an example of the application of our filter in the segmentation of entire brain MRI scans into three classes: white matter, gray matter, and cerebral spinal fluid (CSF). In section 7, we share an example of the application of our filter in the segmentation of the dorsolateral prefrontal cortex (DLPFC).

Due to space constraints, further algorithmic details are currently in submission [3]. In the algorithm paper, it will be shown that removing the skull in the MRI data can help the method of Teo, Saprio, and Wandall [1] give more accurate results, eliminating the need to grow gray matter from the boundary of the white matter.

2 Algorithm Details

In this section, we provide a high-level description of the knowledge-based segmentation algorithm. The algorithm is built upon foundational work found in [1,2,4].

We assume that the value of each voxel intensity in a given class can be considered as a random variable, independent across pixels. In the following results, we assume that the voxel intensities are normally distributed. This assumption may be modified to support other distributions that may better fit the data. With a large set of training data, the distributions may also be learned a priori. The application of the statistical distributions to the voxel intensities produces the data term, $Pr(Vi = v|Ci = c)$. We also assume that the prior likelihood, $Pr(Ci = c)$, of a pixel belonging to a particular class is uniform across all classes. This assumption too may be modified to incorporate other prior knowledge, such as shape priors. With the data and prior terms, we generate the posteriors via Bayes' Rule. The posteriors are then smoothed for 5 iterations using a 3D version of the affine invariant smoother of Olver et. al [5]. Finally, we use the maximum a posteriori estimate to achieve our final segmentation.

The following is a concise description of the algorithm:

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5: Smooth the posterior images for several iterations using an anisotropic, edge-preserving PDE based on the geometric heat equation and renormalize the posterior images after each smoothing iteration
6: Apply maximum a posteriori rule to achieve segmentation labeling

3 Project Status

Several files have been submitted in conjunction with this paper. The current version of the code can be found in KnowledgeBasedSegmentation.cxx. This code is run with 4 command line parameters: input file path, output file path, the number of smoothing iterations, and the number of classes. We are currently writing the ITK filter version of this code.

We have also developed accessory filters to support various segmentation features. Accompanying this paper are itkHistogramDensityFunction.h and itkHistogramDensityFunction.txx which may be used to relax the assumption of normal distribution and apply an arbitrary distribution to the data as discussed in section 2. In order to handle low level image operations, it was also necessary for us to write code to convert from several images of scalars to a single image of vectors. This can be found in itkImageCastVectorIndexSelectionFilter.h.

In the future, a filter version of this code will be available in the Code/Algorithms/ directory of the ITK source tree. We are also in the process of writing accompanying ITK testing and example code, to be included in the ItkSoftwareGuide. Note that the filter uses 12 additional ITK files which can be accessed at http://www.itk.org.

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In this section, we provide the ITK user with details about the use of this segmentation filter. The knowledge-based segmentation filter minimally requires that the user only set the input with an image. All other user accessible parameters are optionally set or accessed and have default values.

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Most important among the optional parameters is the parameter 'nClasses' which may be accessed via Set() and Get() methods. This parameter is an integer that determines the number of classes into which the algorithm will segment the input imagery. This algorithm does not attempt to guess the optimal number of classes into which the imagery should be segmented. Note that due to the use of the itkScalarImageKmeansImageFilter, the actual output image may contain less classes than the user initially requests, but this is a rare condition. The default value for 'nClasses' is 2, resulting in a binary image labeling only foreground and background classes.

4.2 Posterior Smoothing

The user will also have access to the Set() and Get() methods of the smoothing parameters in order to control the smoothing of the posteriors. These parameters include 'nSmoothingIterations', 'timeStep', and 'conductance'. The parameter 'nSmoothingIterations' is an integer which determines the number of smoothing iterations to perform on the posteriors at step 5 of the algorithm. The default value of 'nSmoothingIterations' is 10.

The parameters 'timeStep' and 'conductance' are used by the anisotropic smoothing filter to determine the amount of smoothing to perform on a given iteration. For stability reasons, the time step should typically be less than 0.25. The higher the value, the more smoothing that will occur with each iteration. The default value of 'timeStep' is 0.1. The default value of 'conductance' is 3.0.

5 Results

We present the results of this code on two different projects. First, we show the effect of applying this code to skull-removed brain MRI scans. Second, we show the effect of applying this code to the extraction of the DLPFC from a user-defined subregion of brain MRI data.

We present our results on brain MRI scans, comparing the results of the knowledge-based segmentation to manual segmentations on datasets of schizophrenic patients. The patients' heads were imaged in the coronal plane with a 1.5 T MRI system [1] and a postcontrast 3D sagittal spoiled gradient recalled (SPGR) acquisition with contiguous slices. The resolution is $0.975 \times 0.975 \times 1.5$ mm ($256 \times 256 \times 123$ voxels). The knowledge-based segmentations were obtained with the ITK code, which has been submitted in conjunction with this paper.

All segmentations were done on 2D slices. We compare the knowledge-based segmentation (S) to the ground truth manual segmentation (G) using the DICE coefficient [6]: $DSC(S,G) := \frac{V_{S \cap G}}{\frac{1}{2}(V_S + V_G)}$, where V_X is the volume (number of voxels) of segmentation X. DSC values greater that 0.7 are regarded as good in the literature [6].

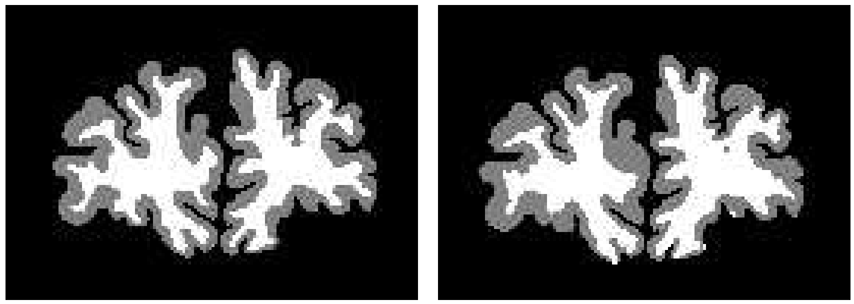
5.1 Brain Volumes

Here we applied the knowledge-based segmentation to 10 datasets of skull-removed imagery. For each case we picked the coronal slice immediately anterior to the temporal lobe tip. The results (white matter mean DSC=0.8842 and gray matter mean DSC=0.8952 for $N = 10$ cases) show that the knowledge-based segmenter gives good results in white matter and gray matter (see Table 1). The results of a typical knowledge-based segmentation compared with the manual-based segmentations for Case 1 are shown in Figure 1(a),1(b) and for Case 2 in Figure 1(c),1(d).

	Case 1	**Case 2**	**Case 3**	**Case 4**	**Case 5**
Slice	96	98	101	104	98
WM DSC	0.8996	0.8558	0.8930	0.8820	0.8910
GM DSC	0.9053	0.8782	0.9114	0.8953	0.9071
	Case 6	**Case 7**	**Case 8**	**Case 9**	**Case 10**
Slice	101	98	97	98	99
WM DSC	0.8916	0.8645	0.9167	0.8885	0.8593
GM DSC	0.8922	0.8991	0.9276	0.8987	0.8372

Table 1. DICE validation measures for white (WM) and gray (GM) matter segmentations on 10 datasets

[1] Signa, GE Medical Systems, Milwaukee, WI.



(a) Manual (Case 1) (b) Knowledge-Based (Case 1)

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Fig. 1.

5.2 DLPFC

The results presented here are from the application of the knowledge-based segmentation as part of a larger algorithm for the semi-automatic segmentation of the dorsolateral prefrontal cortex (DLPFC) [7]. A region of interest (ROI) encapsulating the DLPFC is defined in the raw data during the user-driven, semi-automatic portion of the DLPFC algorithm. Here we show the results of applying the knowledge-based ITK segmentation to the ROI. The DLPFC is the resulting gray matter.

The semi-automatic DLPFC segmentation algorithm is currently being coded into 3D Slicer and our knowledge-based ITK filter will be wrapped in VTK and used in the 3D Slicer module. The results (gray matter mean DSC=0.8230 for $N = 5$ cases) show that the knowledge-based segmenter gives good results (see Table 2). The results of a typical knowledge-based segmentation compared with the manual-based segmentations for Case 1 are shown in Figure 2(a),2(b).

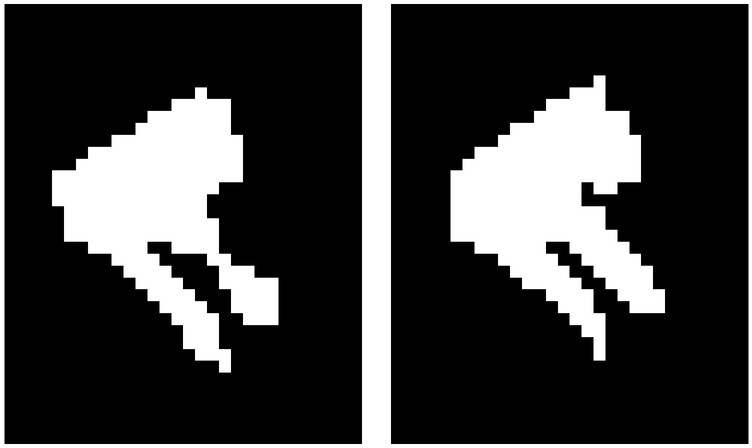

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Fig. 2.

	Case 1	Case 2	Case 3	Case 4	Case 5
GM DSC	0.8119	0.7997	0.8326	0.8344	0.8365

Table 2. DICE validation measures for gray (GM) matter segmentations on 5 datasets

6 Open Source Discussion

The open source nature of this project greatly facilitated the creation of this filter. We were able to leverage existing ITK code to quickly achieve image I/O and iteration functionality. The ITK framework was already in place to handle a myriad of input and output types, greatly extending the usefulness of our code to a variety of image types. Furthermore, existing ITK filters were used to perform K-Means classification, evaluate Gaussian density functions, smooth the posteriors, and convert the labelmap image into 'N' histograms (one for each class). The utilization of these files can be seen in the 12 separate included ITK files.

7 Conclusion

We have presented our ITK knowledge-based segmentation code and shown positive results in two separate applications. User details and project status sections provide the reader with the information necessary to run the accompanying code. Future work will port this code from its current state into an ITK filter.

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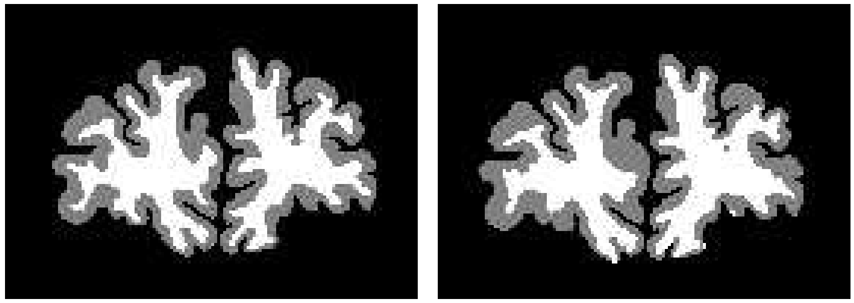

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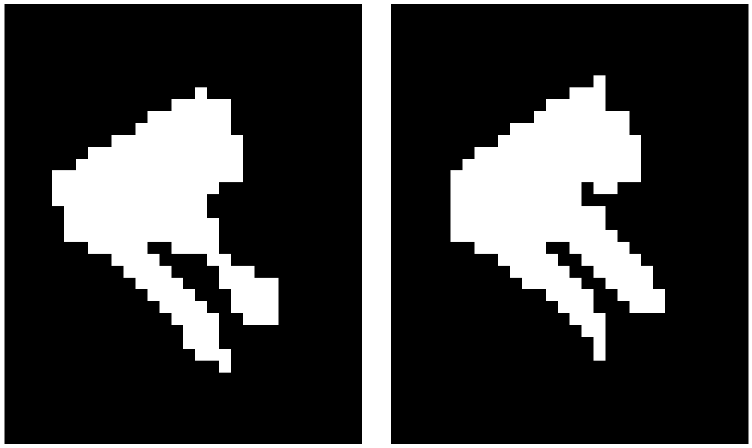

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