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Superpixels in Brain MR Image Analysis

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Abstract— **A large number of sophisticated techniques have been proposed over the last few decades for automatic analysis of brain MR images to help clinicians better diagnose and understand anatomical changes due to neurological disorders. While significant improvements in performance have been achieved, almost all techniques suffer from a common limitation of high computational complexity due to the large number of voxels present in a typical MR volume. Computational complexity is a major hurdle in the clinical application of these sophisticated image analysis techniques. Brain MR volumes consist of approximately piecewise constant tissue regions with high redundancy among voxel intensities, which can be grouped into perceptually meaningful entities (superpixels) to reduce the complexity. In this study, we investigate the utility of superpixels (2D) and supervoxels (3D) in reducing computational complexity of brain MR analysis tasks. We investigate the extent of spatial and intensity distortions introduced in superpixel representation of MR images and evaluate its effect on brain tissue segmentation as an example task. We observe that superpixels are highly promising for significantly reducing the computational complexity of the lower-level image analysis tasks that are often essential components of MR analysis pipelines.**

I. INTRODUCTION

Magnetic Resonance Imaging (MRI) produces large amounts of data that is difficult to interpret through manual inspection. This has motivated the development of sophisticated computer-based tools that can extract clinically relevant information from brain MR data and better present it to physicians. Such tools typically consist of a series of low-level image analysis tasks (such as tissue segmentation, denoising and bias field removal) that preprocess MR volumes for reliable feature extraction. While state of the art algorithms illustrate fairly good performance, a common problem associated with most methods has been high computational complexity, which is expected to further exacerbate as advances in MR imaging produce higher resolution images with more MR voxels. A combination of these low-level analysis tasks with high complexities limits the clinical application of any such computer-based tool.

The problem of high computational complexity can potentially be addressed by grouping MR voxels with high redundancy in features such as texture and intensity, since they are likely to belong to the same physical world object. This concept is known as *superpixels* in the field of computer vision. Unlike some other medical images (such as mammograms), brain MR images contain approximately piecewise constant regions that can be represented using superpixels and, thereby, address the problem of high computational complexity associated with the low-level image analysis techniques. To the best of our knowledge, superpixels have never been explored in brain MR image analysis.

Superpixels need to have several important properties before they can be considered for application in MR image analysis. First, superpixel representation should not distort the important anatomical details in MR images that could affect the performance of subsequent image analysis tasks. Thus the superpixel representation should have strong spatial adherence to the tissue boundaries in MR images and cause minimal loss of intensity information. Second, superpixel generation in itself should have low complexity, and should significantly reduce the complexity of subsequent image analyses. Third, several MR image analysis tasks utilize neighborhood relationships and, thus, superpixels should be compact (or regular) in shape. Irregular superpixels tend to share boundaries with several other superpixels and, therefore, are unsuitable for defining such neighborhood relationships. While all these properties are desirable, there is an interplay between the superpixel compactness, boundary adherence, intensity distortion and complexity reduction that must be balanced.

In this study, we investigated the utility of superpixels (and supervoxels) for reducing the complexity of MR analysis tasks. We quantitatively evaluated the ability of superpixels to adhere to tissue boundaries and preserve intensity information in MR images. We studied the relationship between spatial/intensity distortions from superpixel representation and the reduction in computational complexity achieved for subsequent image analysis tasks. As an example of application to low-level MR analyses, we also demonstrated the utility of superpixel representation in brain tissue segmentation and studied its implications on the speed and accuracy of the task.

II. METHODS

A. Evaluation of Superpixel Techniques

We evaluate the most popular superpixel generation approaches for application in brain MR analysis. Normalized cuts (N-cuts) approach [1] recursively partitions an image pixel graph by minimizing a cost function defined on the partition boundaries. N-cuts produces very compact superpixels but suffers from high complexity $O(N^{3/2})$ and poor boundary adherence. Quick shift [2] is a mode-seeking algorithm

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that forms a tree of links with the nearest neighbor increasing the Parzen density estimate. Quick shift has good boundary adherence but suffers from high complexity O(dN^2) (d is a constant) and provides no means to control the compactness of superpixels generated. Felzenszwalb et al. [3] proposed an approach based on agglomerative clustering such that superpixels are the minimum spanning tree of constituent pixels. They show good boundary adherence, but the method suffers from high complexity O($N\log N$) and produces irregular superpixels. Most of these approaches also do not provide any control over the number of desired superpixels.

Achanta et al. [4] recently proposed *simple linear iterative clustering* (SLIC), which performs a constrained search space k-means clustering on the voxel intensities and spatial locations to generate superpixels. SLIC is fast (O(N)), produces compact superpixels, allows control over the number of desired superpixels and has good boundary adherence [4]. This makes SLIC an ideal choice for investigating the significance of superpixels in brain MR image analysis tasks. We briefly describe SLIC algorithm in the next section.

B. SLIC Superpixels and Supervoxels

Notation : N represents the total number of MR voxels, C represents the desired reduction in complexity, and $k = N/C$ represents the number of superpixels.
Initialization : The initial superpixel centers $S_j = [I_{s_j}, x_{s_j}, y_{s_j}]^T$ are sampled uniformly on the image domain at a grid interval of $\sqrt{N/k}$, where I_{s_j} and (x_{s_j}, y_{s_j}) represent the intensity and spatial location of superpixel centers, respectively. Superpixel centers are moved to the lowest gradient position in a 3×3 neighborhood to avoid centering a superpixel on an edge or seeding with a noisy pixel.
Assignment : Image voxels v_i are assigned to the closest superpixel center within a search space of $2S \times 2S$ around the voxel. The distance D to a superpixel center is defined as,

$$D = \sqrt{\left(\frac{d_c}{m}\right)^2 + \left(\frac{d_s}{S}\right)^2} \qquad (1)$$

where, $d_s = \sqrt{(x_{c_j} - x_i)^2 + (y_{c_j} - y_i)^2}$ and $d_c = \sqrt{(I_{c_j} - I_i)^2}$; $v_i = [I_i, x_i, y_i]^T$ and $S_j = [I_{s_j}, x_{s_j}, y_{s_j}]^T$ correspond to the i^{th} voxel and j^{th} superpixel, respectively.
Update : Superpixel centers S_j are adjusted to the mean vector $[I_i, x_i, y_i]^T$ of all the voxels belonging to the cluster.
Convergence : Assignment and update steps are repeated iteratively until the residual error, calculated as the L_2 norm between the new and older superpixel centers, converges.

In this study, we investigated the application of superpixels and supervoxels in brain MR image analysis. 2D superpixels are generated independently for every MR image slice and then combined to represent the whole MR volume. The concept of superpixels can be easily extended to supervoxels (in 3D) by including depth dimension in the spatial distance term d_s. 3D supervoxels are computed directly on the MR volume additionally utilizing the depth information in reducing image redundancy.

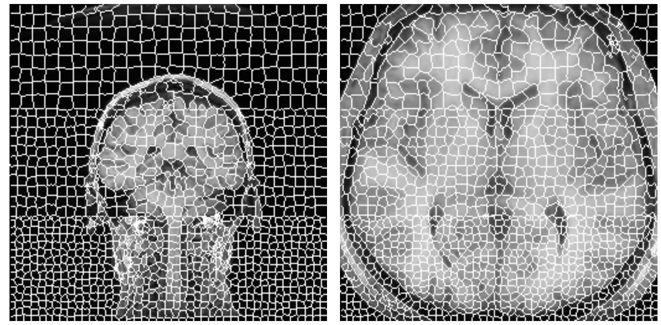


Fig. 1: Sample MR image slices segmented using SLIC into $k = 500, 1000$, and 2000 superpixels.

C. Application in Brain Tissue Segmentation

We considered the low-level image analysis task of brain tissue segmentation and investigated the effect of superpixel/supervoxel representation on its accuracy. We assumed voxel intensities as normally distributed inside each tissue class T_j and classified MR voxels v_i by minimizing the negative joint log-likelihood over the entire image,

$$L = \sum_j \sum_{v \in T_j} \left[\log(\sigma_j) + \frac{(I(v) - \mu_j)^2}{2\sigma_j^2}\right]$$

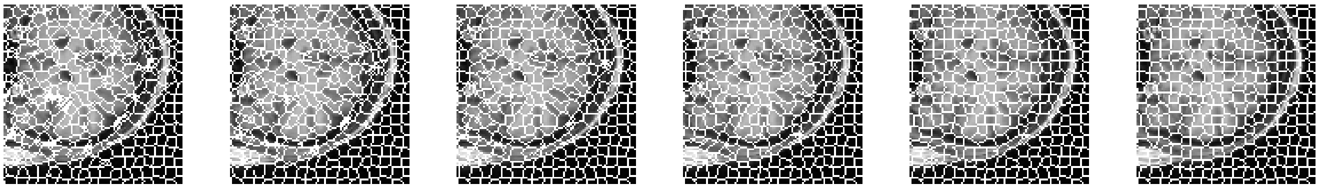
where, μ_j and σ_j denote the mean and covariance matrices of tissue class T_j, respectively. When segmenting brain MRI represented using superpixels, voxels v can be replaced with superpixels S. We quantify the segmentation accuracy by calculating the Jaccard overlap metric $J(A, B) = |A \cap B|/|A \cup B|$ between the obtained tissue segmentation (A) and the expert ground truth segmentation (B). While spatial information in the form of class priors can be included to improve segmentation performance, the primary objective here is to study the effect of image distortion due to superpixel representation on the performance of image analysis tasks. Therefore, we used an objective function defined solely based on intensities to drive brain tissue segmentation. The objective function is minimized using graph cuts in this study.

III. EXPERIMENTS & RESULTS

Using two real datasets, we investigated (i) the ability of superpixels to spatially adhere to tissue boundaries in MR images, (ii) the local loss of intensity information due to superpixel representation, (iii) the effect of any superpixel induced distortion on the performance of brain tissue segmentation, and (iv) the improvement in computational complexity from the use of superpixel representation.

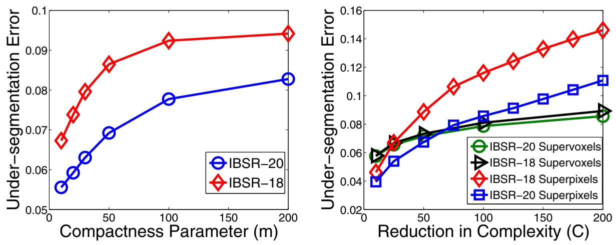
A. Data

We consider two well-established real brain MR datasets obtained from the Internet Brain Segmentation Repository (IBSR) to investigate the significance of superpixels in brain MR image analysis. These datasets contain expert ground truth tissue segmentations (WM, GM, and CSF). IBSR-20 contains 20 normal brain MR volumes collected using 1.5



(a) $m = 10$ (b) $m = 20$ (c) $m = 30$ (d) $m = 50$ (e) $m = 100$ (f) $m = 200$

Fig. 2: Visual illustration of superpixels generated at different levels of compactness parameter m.



(a) (b)

Fig. 3: Average under-segmentation error across IBSR-18 and IBSR-20 subjects for different levels of (a) compactness parameter m (using $k = 2000$), and (b) reduction in complexity C using superpixels and supervoxels ($m = 30$).

Tesla scans with slice thickness of 3.1mm, whereas IBSR-18 contains 18 normal brain MR volumes collected using 3 Tesla imaging system with slice thickness of 1.5mm.

B. Adherence to MR Tissue Boundaries

We studied the interplay between the boundary adherence, complexity reduction (C), and superpixel compactness (m) to obtain a balance between these three properties for accurate MR image representation. We quantified the boundary adherence ability of SLIC superpixels using *under-segmentation error* defined as,

$$U = \frac{1}{N}\left[\sum_{i=1}^{M}\left(\sum_{s_j|s_j\cap g_i>B}|s_j|\right) - N\right]$$

where, M is the number of ground truth regions, g_i denotes the i^{th} ground truth segmentation, and $s_j|s_j \cap g_i$ represents the superpixel set that represents the region g_i. B is a minimum threshold of overlapping pixels between s_j and g_i that accounts for any ambiguities in the ground truth and is set to 5% of $|s_j|$ in our experiments (similar to [4]). U measures the leakage of superpixels across tissue boundaries and has been widely used in the computer vision literature [4], [5], [6].

First, we studied the effect of the compactness parameter m on the boundary adherence ability of superpixels (U). Fig. 2 visually illustrates that higher values of m correspond to more regular and grid-like superpixel structure; however, higher m also adversely affects the boundary adherence of superpixels (Fig. 3a). Next, we studied the relationship between reduction in complexity C (or superpixel number k) and the boundary adherence of superpixels. Fig. 3b shows that U increases with increase in complexity reduction C. This was also illustrated in Fig. 1 where higher k better captured the finer details in MR images. We also compared the boundary adherence of superpixels with supervoxels (Fig. 3b). While superpixels show better boundary adherence ability at small values of C, supervoxels show much better boundary adherence for higher complexity reduction. Supervoxels illustrated much higher stability in boundary adherence with increase in C and achieved much higher reduction in complexity ($C \approx 200$) in comparison with superpixels ($C \approx 75$) maintaining the same levels of U.

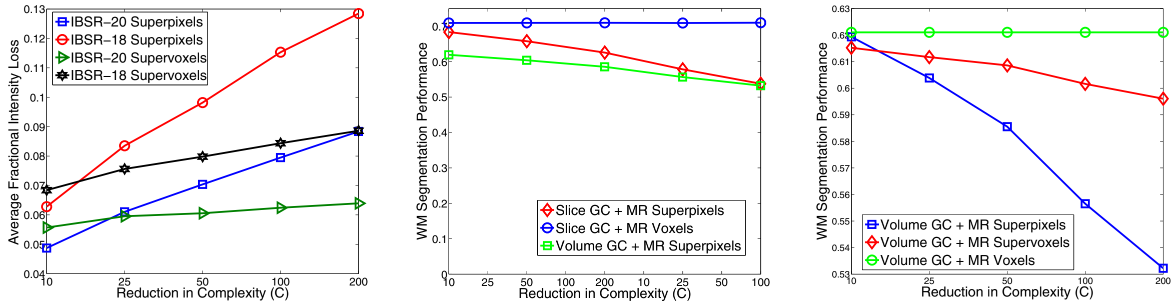
Boundary adherence should not be affected by the presence of bias field in MR images, as long as a sufficient number of superpixels are used to represent the image, because the slowly varying bias field has negligible effect when the superpixel size S is small ($S \propto 1/\sqrt{k}$). We tested this hypothesis by calculating the difference in under-segmentation error ΔU between MR volumes containing high levels of bias field and MR volumes without any significant bias field using the IBSR-20 dataset. We observed very little difference $\Delta U < 0.005$ when MR images are represented using $k > 1500$. As expected, ΔU increased when the number of superpixels was small (for $k < 500$, $\Delta U > 0.025$).

C. Local Loss in Intensity Information

Superpixel representations result in local loss of intensity information, which can be thought of as intensity distortion. We quantified the loss in local intensity information due to the superpixel/supervoxel representations using average fractional intensity loss (AFL),

$$AFL = \frac{1}{N}\sum_{i=1}^{N}\frac{|I_{S(v_i)} - I_{v_i}|}{I_{v_i}}$$

where, I_{v_i} and $I_{S(v_i)}$ represent the intensity values of MR voxel v_i and superpixel $S(v_i)$ containing the i^{th} voxel, respectively. Fig. 4a shows AFL values for the IBSR-18 and IBSR-20 datasets using superpixels and supervoxels. We observe that while superpixels more accurately represent MR images at lower values of C, supervoxels provided more meaningful image representations when higher complexity reduction is desired.



(a) (b) (c)

Fig. 4: Plots showing the variation of (a) Average loss in local intensity information, and (b) White matter (WM) segmentation performance on IBSR-20 from MR representation using superpixels and supervoxels at different levels of complexity reduction (C). Slice GC and volume GC (in (c)) correspond to slice-wise segmentation and volumetric segmentation using graph cuts (GC) respectively. GM and CSF segmentations show similar trend and, therefore, are not shown separately here.

D. Effect on Brain Tissue Segmentation Performance

Brain MR segmentation can be performed either slice-wise (Slice GC) or volumetrically using all MR voxels (Volume GC). Fig. 4b and Fig. 4c show that slice-wise segmentations (Slice GC + MR Voxels) have higher accuracies than volumetric segmentations (Volume GC + MR Voxels). This is due to the presence of bias field in MR volumes whose effects are less deteriorating when only slice-wise data are considered for segmentation. The effect of superpixel representation was investigated by comparing the segmentation accuracy obtained using superpixels against the segmentation accuracy obtained using MR voxels. Fig. 4b shows that the segmentation accuracy obtained on superpixel representation rapidly decreased with increase in C, which is expected due the combined effects of decreased boundary adherence (Fig. 3b) and increased intensity distortion (Fig. 4a). We also observed that the rate of decline in segmentation performance is much less in supervoxels (Volume GC + MR Supervoxels) than in superpixels (Volume GC + MR Superpixels).

E. Complexity Reduction using Superpixels & Supervoxels

We observed consistent patterns of MR representation accuracy at different levels of complexity reduction using superpixels and supervoxels. Superpixels are more efficient for low levels of complexity reduction ($C < 15$) and show little spatial and intensity distortion ($U < 5\%$, $AFL < 7\%$). As a result, superpixels support accurate tissue segmentation performance ($\Delta J^{WM} < 0.03$), while reducing the complexity by approximately 15 times. In image analysis tasks (such as bias field removal) where MR distortions do not have significant effects on the task performance, supervoxels can achieve large reductions in complexity while still preserving most of the important anatomical details in MR images. For instance on the IBSR-20 dataset, supervoxels achieved 200-fold reduction in complexity, while achieving good boundary adherence ($U < 9\%$), low intensity distortion ($AFL < 6\%$), and only a small decrease in segmentation performance ($\Delta J^{WM} \approx 0.02$) for volumetric segmentations.

IV. CONCLUSION

In this study, we investigated the utility of superpixels and supervoxels in low-level brain MR analysis tasks using two real MR datasets. We evaluated the accuracy of superpixels for brain MR image representation based on their boundary adherence and their ability to retain important intensity information. We also investigated the effects of superpixel representation on the reduction in complexity and performance of brain tissue segmentation as an example of an MR image analysis task. We showed that superpixels and supervoxels are highly promising for significantly reducing computational complexity of low-level MR analysis tasks (such as tissue segmentation, denoising, and bias field removal) with little effects on task performance.

ACKNOWLEDGMENT

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