Atlas Construction via Dictionary Learning and Group Sparsity

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Abstract. Atlas construction generally includes first an image registration step to normalize all images into a common space and then an atlas building step to fuse all the aligned images. Although numerous atlas construction studies have been performed to improve the accuracy of image registration step, simple averaging or weighted averaging is often used for the atlas building step. In this paper, we propose a novel patch-based sparse representation method for atlas construction, especially for the atlas building step. By taking advantage of local sparse representation, more distinct anatomical details can be revealed in the built atlas. Also, together with the constraint on group structure of representations and the use of overlapping patches, anatomical consistency between neighboring patches can be ensured. The proposed method has been applied to 73 neonatal MR images with poor spatial resolution and low tissue contrast, for building unbiased neonatal brain atlas. Experimental results demonstrate that the proposed method can enhance the quality of built atlas by discovering more anatomical details especially in cortical regions, and perform better in a neonatal data normalization application, compared to other existing start-of-the-art nonlinear neonatal brain atlases.

1 Introduction

Brain atlases are widely used in the neuroimaging field for disease diagnosis, surgical planning, and educational purpose. Usually, an atlas is created as an average model to represent a population normalized in a common space. Specifically, constructing an atlas needs **1)** an image registration step to normalize all images in the population into a common space and **2)** an atlas building step to fuse all aligned images together. Note that the subject-dependent anatomical details, especially in the cortical regions, may be smoothed out during the image averaging process in the atlas building step.

Many studies have been performed for atlas construction, with main efforts placed on the image registration step. If images in the population can be well aligned, less

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structural discrepancies between aligned images will be obtained and thus the built atlas will keep more anatomical details. Previously, atlas construction is often performed by first choosing one image as a template and then nonlinearly registering all other images to the selected template. This approach could lead to bias in the atlas construction, since the resulting atlas is generally optimized to be similar with the selected template and will has different appearance when different templates are used in registration changes. Thus, groupwise registration is recently proposed to overcome the limitation of template selection, which estimates the geometric mean of the population as the atlas by iteratively performing the step of registering images to the tentatively-estimated atlas and the step of averaging the tentatively-aligned images as new atlas [1]. With the use of groupwise registration, unbiased atlas can be constructed. However, all the aligned images are often simply averaged equally or with some weights for building the atlas. Actually, including all images in the population for building atlas may only marginally improve the details of atlas, but at the risk of introducing more noises and thus making the averaged anatomical structures blurry.

On the other hand, sparse representation has been recently proposed as a powerful tool for robustly representing high-dimensional signals using a small set of basis functions in an over-complete dictionary [2]. This method was developed based on a simple concept that the underlying representations of many real-world images are often sparse, as evidenced by the human biological vision processing system [3]. Sparse representation has several advantages. *First*, the input image can be represented as a linear combination of a small number of basis functions. *Second*, the dictionary with basis functions can be made over-complete to offer a wide range of representing elements. Super-resolution image construction, as a special application of sparse representation, is also an active area of research in computer vision, for recovering a high-resolution image from one or more low-resolution images [4].

In this paper, we propose a novel patch-based sparse representation method for atlas construction, to specially improve the performance of the atlas building step. We hypothesize that, by sparsely representing each patch of the atlas using a small number of image patches, instead of all patches in the whole population, more anatomical details can be revealed and finally an atlas can be obtained. In our implementation, the atlas is constructed locally in a patch-by-patch fashion to ensure the local representativeness, and also the neighboring patches are constrained to have similar representations by using the group sparsity strategy. The overlapping patches are further employed to ensure the structural consistency along the patch boundaries. We apply our proposed method to the neonatal MRI data which often have poor spatial-resolution and low tissue-contrast, thus challenging for building sharp atlas. Experimental results indicate, both qualitatively and quantitatively, that our proposed method can produce much higher quality atlas, compared to the other existing state-of-the-art neonatal atlases.

2 Method

2.1 Overview

In this paper, we consider the atlas construction as image representation problem, with goal of generating representative detailed brain structures from a population of subject images. To do this, we first employ a recently-developed unbiased groupwise registration method to align all subject images onto a common space, and then put our main efforts to introduce our proposed atlas building step. Specifically, for each patch in the to-be-built atlas, a patch dictionary is first adaptively constructed by including the current patch as well as neighboring patches from all aligned subject images. In this way, this dictionary will contain sufficient elements (or local patches) for representation of each atlas patch, under guidance that the reconstructed atlas patch should be similar to the corresponding patches of the subject images distributed near to the population center. By also requiring similar sparse representation for nearby patches in the atlas by using group sparsity, and further making nearby patches to be spatially overlapped, super-resolution brain atlas can be constructed by combining all the reconstructed patches. In the following, details for unbiased groupwise registration, patch-based representation, and group regularization on neighboring patches will be discussed.

2.2 Unbiased Groupwise Registration

This step is to spatially normalize all subject images into a common space, which is a necessary initial step for subsequent atlas building. Unlike the pairwise registration method that needs selection of initial template, groupwise registration is free of template selection and is able to simultaneously register all subject images onto the hidden common space. Although many groupwise registration methods developed in the literature can be employed for our study, we decided to use a state-of-the-art groupwise registration method in [1] for aligning our images, since its software package is freely available at http://www.nitrc.org/projects/glirt. Also, this groupwise registration method used (1) attribute vector as morphological signature of each voxel for guiding accurate correspondence detection among all subject images, and (2) also a hierarchical process for selecting a small number of critical voxels (with distinctive attribute vectors) to guide the whole registration. In this way, the high quality of groupwise registration results can be achieved.

2.3 Patch-Based Representation

We employ a patch-based representation technique for atlas construction, due to its two characteristics. *First*, local anatomical structure could be better captured in a small patch than in a large brain region. *Second*, patch size can be optimized to compromise the local structure representativeness and global structure consistency. We sample local cubic patches to cover the whole brain image. At each point, we can obtain patches $\{p_i | i = 1, \dots, N\}$ from all aligned images, where N is the total number of images. Note that each patch is represented with a vector consisting of $M = s \times s \times s$ features (i.e., intensities), where s is the size of patch at each dimension.

We consider all local patches are highly correlated and thus their distribution can be estimated in Euclidean space. The group center of patches is approximated as the group mean of all patches, i.e., $\frac{1}{N}\sum_i^N p_i$. In this feature space, some patches may distribute near the group center, while others may be far away. Generally, patches near the group center have more agreement in representing the population mean, while patches far-away from the group center may introduce anatomical discrepancies and thus make the group mean image or atlas blur. Inspired by this observation, we select K ($< N$) nearest patches to the group center, denoted as $\{y_k | k = 1, \dots, K\}$, where the similarity between patches is measured by image correlation coefficient. To formulate the atlas building (or the estimation of group mean image) as a representation problem, for each to-be-estimated patch in the atlas, we require it to represent the common anatomical structure of all K nearest patches simultaneously.

To achieve this, we need to first build a dictionary for each atlas patch under reconstruction. An initial dictionary can include all patches with same location in all aligned images, i.e., $D = [p_1, p_2, \dots, p_N]$. To further overcome the possible registration error, the initial dictionary is extended to include more patches from the neighboring locations, thus providing a sufficient number of elements for powerful representation. In this application, we include 26 immediate neighboring locations. Thus, for each aligned image, we will take totally $g = 27$ patches; and from all N aligned images, we will include totally $\bar{N} = g \times N$ patches in the dictionary D.

Then, we can require the reconstructed atlas patch, sparsely represented by the coefficient vector x and the dictionary D, to be similar to all K patches denoted by Y that are closer to the group mean. This problem can be formulated as the following minimization problem:

$$\hat{x} = arg \min_{x>0} \left[\sum_{k=1}^{K} \|Dx - y_k\|_2^2 + \lambda \|x\|_1 \right] \tag{1}$$

where $D \in \mathbb{R}^{M \times \bar{N}}$, $x \in \mathbb{R}^{\bar{N} \times 1}$, $y_k \in \mathbb{R}^{M \times 1}$. The first term measures the discrepancy between observation y_k and the reconstructed atlas patch Dx, and the second term is L_1 regularization of the coefficient vector x (also called LASSO) [5]. Sparsity is encouraged in x under LASSO. $\lambda \geq 0$ is a parameter controlling the influence of the regularization term.

2.4 Group Regularization on Neighboring Patches

Generally, neighboring patches should share similar representations, in order to achieve local structure consistency for the reconstructed atlas. Thus, group sparsity regularization, namely group LASSO [6], is introduced. Specifically, besides solving the representation task for the current patch, we also consider solving the representation tasks in all 26 neighboring patches simultaneously, constraining the coefficients for the whole group.

Denote $g = 27$ as the total number of patches, and let D_{G_j}, and y_{k,G_j}, and x_{G_j} denote the respective dictionary, observation variable, and coefficient vector of the j-th patch, respectively, with $j = 1, 2, \dots, g$. For simplicity, we use $X = \left[x_{G_1}, x_{G_2}, \dots, x_{G_g}\right]$ as a matrix containing all coefficient column vectors. Note that the matrix can also be written in the form of row vectors $X = [u_1; u_2; \dots; u_{\bar{N}}]$, where u_i is the i-th row in the matrix X. Then, we reformulate the Eq. (1) into a group LASSO problem as below:

$$\hat{x} = arg\min_{x>0}\left[\sum\nolimits_{j=1}^{g}\sum\nolimits_{k=1}^{K}\left\|D_{G_j}x_{G_j} - y_{k,G_j}\right\|_2^2 + \lambda\|X\|_{2,1}\right] \quad (2)$$

where $\|X\|_{2,1} = \sum_{i=1}^{\bar{N}}\|u_i\|_2$. The first term is a multi-task least square minimizer for all the g groups. The second term is for regularization. The $\|X\|_{2,1}$ is a combination of both L_2 and L_1 norms, in which the L_2 norm is imposed to each row of the matrix X (i.e., u_i) to make the neighboring patches have similar representations while the L_1 norm is imposed to the results of L_2 norm to ensure the sparsity of the representation by the respective dictionary (reflected by the sum of $\|u_i\|_2$). In this way, the nearby patches share the same sparsity pattern in finding their representations. The group LASSO in Eq. (2) can be solved efficiently by using algorithm in [6].

Using non-overlapping patches could result in steep gradient changes along patch boundaries and also inconsistent structures across patches. Thus, to alleviate this problem, overlapping patches are used here by taking average from multiple results for each voxel. Specifically, we sample patches in the whole brain by moving the current patch point for half patch size at each time. By doing so, each voxel is now included by 8 patches. Then, by combining all overlapping patches together, the atlas can be finally obtained.

3 Experiments

3.1 Data Specification

Data for Atlas Construction. Neonatal data generally has low spatial resolution and insufficient tissue contrast, and would considerably benefit from the proposed method for building an atlas. Specifically, 73 healthy neonatal subjects (42 males/31 females) were recruited, and their MR images were scanned at 33-42 gestational weeks. MR images were acquired on a Siemens head-only 3T scanner with a circular polarized head coil. T2-weighted images were obtained with 70 transverse slices using turbo spin-echo (TSE) sequences: TR=7380 ms, TE=119 ms, Flip Angle=150°, and resolution=1.25×1.25×1.95 mm^3. The study has been proved by IRB and the written informed consent forms were also obtained from all parents. All the 73 neonatal images were resampled into 1×1×1 mm^3, bias corrected, skull stripped [7], and tissue segmented [8].

Data for Normalization Evaluation. We evaluate the performance of proposed atlas with other state-of-the-art neonatal atlases by measuring how well they are able to spatially normalize a neonatal population. MR images of 20 healthy neonatal subjects (10 males/10 females) were obtained at 40±1 (37-41) gestational weeks, using TSE sequences with parameters: TR=6200 ms, TE=116 ms, Flip Angle=150°, and resolution=1.25×1.25×1.95 mm^3. All the images were resampled into 1×1×1 mm^3, bias corrected, skull stripped [7], and tissue segmented [8].

3.2 Parameter Settings

Fig. 1 shows our constructed atlases as functions of patch size and the number of nearest subjects to the group mean image. Generally, larger patch size will affect the ability of local representation and make the atlas more blur. In our experiments, we use 6×6×6 patches with overlap of 3 voxels between adjacent patches. We choose $K = 10$ center subjects, as observed from experiments that, if K is too large, the resulting atlas will appear blur, while if K is too small, e.g., $K = 2$, the resulting atlas can be easily affected by noises. Regularization parameter was set as $\lambda = 0.01$, since too high regularization values will reduce the number of non-zero coefficients in patch representation and thus become unstable.

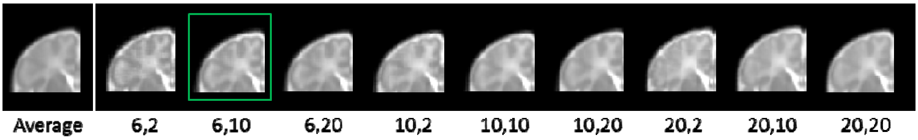

Fig. 1. Close-up views of our constructed atlases. The number (d,K) in this figure represents patch size and the number of center subjects, with (6,10) chosen in this paper. Average of all aligned images is also shown in the left panel for comparison.

3.3 Experimental Results

Fig. 2 compare results obtained with different atlas construction methods. Top row shows the axial views of the constructed atlases, and bottom row shows the close-up views of the top-left part of brain region. Patch size is set as 6×6×6 with 3 voxels overlap between patches. As we can see, the result obtained from the average of 10 center images (adaptive at each local patch) (Fig. 2b) shows higher level of details than the result from the average of all images (Fig. 2a), while it still suffers from steep gradient changes along patch boundaries (or boundary effect) and inconsistent intensities between neighboring patches. Better structural consistency is observed in the result by sparse representation (Fig. 2c), and further enhanced in the result by using group sparsity (Fig. 2d).

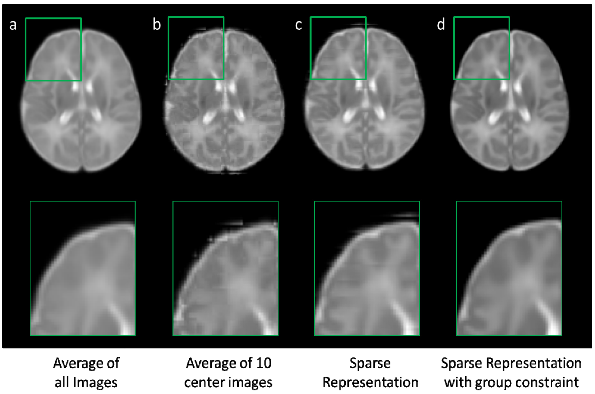

Fig. 2. Comparison of atlases built by different construction methods. Note that the atlases in (b-d) are constructed in a patch-by-patch fashion.

Comparison with Other State-of-the-Art Neonatal Atlases. The proposed atlas is further compared with other state-of-the-art neonatal atlases constructed by nonlinear registration techniques. Typical views of atlases are shown in Fig. 3. Kuklisova-Murgasova *et al* [9] created a 4D atlas using 142 neonatal subjects between 29 and 44 gestational weeks, in which the atlas for 41 weeks was used and referred here to as Atlas-A. Oishi *et al* [10] constructed atlas using 25 brain images from neonates of 38-41 post-conceptional weeks, here referred to as Atlas-B. Serag *et al* [11] also made a 4D atlas using 204 premature neonates between 26.7 to 44.3 gestational weeks, in which the atlas for 41 weeks was used and referred here to as Atlas-C. Average atlas of our 73 aligned neonate images is also provided by simply averaging them. Our proposed atlas, constructed from 73 neonates using sparse representation with group constraints, establishes the highest level of details than any other neonatal atlases.

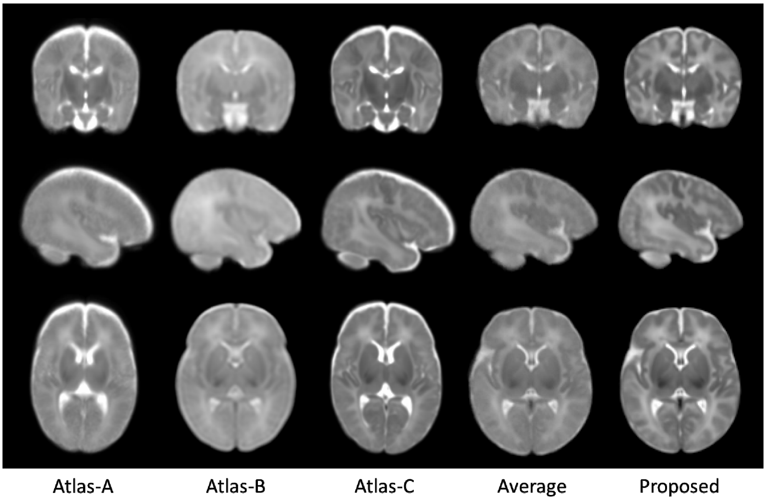

Fig. 3. Comparison of nonlinear neonatal atlases among the results from Kuklisova-Murgasova *et al* (2010) (Atlas-A), Oishi *et al* (2011) (Atlas-B), Serag *et al* (2012) (Atlas-C), equal averaging of 73 aligned images (Average), and our proposed method (Proposed). Similar slices were selected directly from these 5 atlases for easy comparison.

Evaluation of Atlas Quality through Image Registration. To quantitatively evaluate the quality of our atlas, we also design an experiment to spatially normalize a population of neonatal images separately by using the 5 atlases shown in Fig. 3 as templates. In this experiment, we use 20 neonates as detailed in Data subsection which are independent of the data used for atlas construction. All images were aligned to the 5 atlases using a nonlinear registration method, Diffeomorphic Demons [12], respectively. Registration parameters were conservatively set as 5×5×5 iterations and 3 smoothing sigma for the deformation field. Brain tissues, i.e., gray matter (GM), white matter (WM), and ventricular cerebrospinal fluid (CSF) in segmented images, were also aligned to the common space by using the deformation fields. Since the ground truth for normalization is not available, we generate a mean image representing the common structures of population by using voxel-wise majority voting on the 20 aligned segmented images. Brain tissues of each warped image were then compared with the mean image, and the structural agreement was assessed by the Dice coefficient.

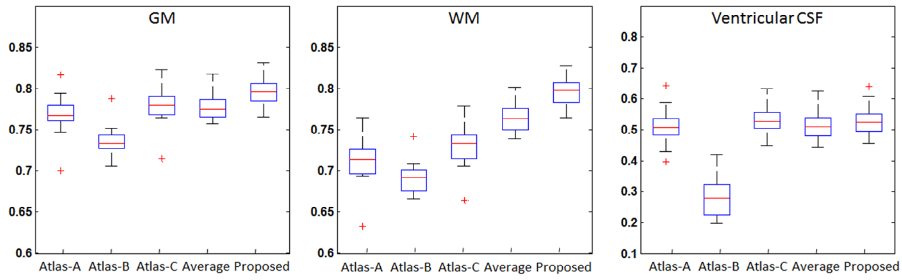

Fig. 4. Dice coefficients of structural consistency between the warped images and their respective mean image for each of 5 atlases, respectively

Results are shown in Fig. 4. The performance of our proposed atlas outperforms other 4 atlases for GM and WM ($p<0.05$), while no difference for CSF when compared to Atlas-A, Atlas-B, and Average atlas. Average atlas has similar performance with Atlas-A and Atlas-C for GM and CSF, while superior for WM consistency.

4 Conclusion and Future Work

We have presented a novel patch-based sparse representation method for atlas construction, focusing on the improvement of the atlas building step by employing sparse representation and group sparsity techniques. To the best of our knowledge, the present paper is the first work of exploiting sparse representation for building atlases. Experimental results have shown that the local sparse representation method can improve the anatomical details in the constructed neonatal atlas. Our method is flexible enough to be incorporated into any registration algorithms to further improve the atlas quality. Note that a potential limitation of experiment is that the testing data has similar imaging protocol with the data used for our atlas construction, and thus may favor the proposed atlas. In the future work, we would run evaluations on more datasets.

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