SPARSE REPRESENTATIONS AND DICTIONARY LEARNING BASED LONGITUDINAL SEGMENTATION OF MULTIPLE SCLEROSIS LESIONS

Hrishikesh Deshpande, Pierre Maurel, Christian Barillot

Inria, VisAGeS INSERM U746, IRISA UMR CNRS 6074, University of Rennes-1, Rennes, France

ABSTRACT

Sparse representations allow modeling data using a few basis elements of an over-complete dictionary and have been used in many image processing applications. We propose to use the sparse representation and dictionary learning paradigm to automatically segment Multiple Sclerosis (MS) lesions from longitudinal MR data. The dictionaries are learned for the lesion and healthy brain tissue classes, and a reconstruction error based classification approach is proposed for validation on challenge data set.

***Index Terms*—** Sparse Representations, Dictionary Learning, Magnetic Resonance Imaging

1. INTRODUCTION

Multiple sclerosis is a chronic and autoimmune disease of the central nervous system and is characterized by structural damage of axons. MRI is the best paraclinical method for the diagnosis of MS and treatment efficacy. However, manual segmentation of MS lesions is a complex and time consuming task. In the past, several MS lesion segmentation methods have been proposed, with an objective of handling large variety of MR data and which can provide results that correlate well with expert analysis [1]. These methods use different image features, classification methods and lesion models.

Over the last few years, modeling signals using sparse representation and dictionary learning framework has achieved promising results in image classification [2]. Recently, its applications in disease detection have started evolving [3,4]. We propose to explore the use of dictionary learning and sparse representation techniques for the segmentation of MS lesions in longitudinal data set.

In our approach, we learn class specific dictionaries for the lesion and healthy brain tissues. Each dictionary promotes the sparse representation of the class data. The lesion patches are well adapted to its own class dictionary, as opposed to the other. We then use the reconstruction error derived from sparse decomposition of test patch on to these dictionaries for classification. The size of the dictionaries play major role in data representation as well as classification. In the data set, the healthy class patches exhibit more variability as compared to the patches from the lesion class. Thus we use different dictionary sizes for modeling image patches for each class.

2. SPARSE CODING AND DICTIONARY LEARNING

Sparse coding is the process of finding a sparse coefficient vector $\mathbf{a} \in \mathbb{R}^K$ for representing a given signal $\mathbf{x} \in \mathbb{R}^N$ using a few atoms of an over-complete dictionary $\mathbf{D} \in \mathbb{R}^{N \times K}$. It is given by $min_{\mathbf{a}} \|\mathbf{a}\|_0$ s.t. $\|\mathbf{x} - \mathbf{D}\mathbf{a}\|_2^2 \leq \varepsilon$, where $\|.\|_0$ denotes the l_0 norm and ε is the error in representation. Replacement of l_0 norm with the l_1 norm also results in sparse solution [5]. The sparse coding problem can then be given by

$$\min_{\mathbf{a}} \|\mathbf{x} - \mathbf{D}\mathbf{a}\|_2^2 + \lambda \|\mathbf{a}\|_1 , \tag{1}$$

where λ balances the trade-off between the error and sparsity.

For a set of signals $\{\mathbf{x}_i\}_{i=1,.,m}$, we can find a dictionary $\mathbf{D}$ from the underlying data, such that each signal is represented by a sparse linear combination of its atoms. It is given by

$$\min_{\mathbf{D},\{\mathbf{a}_i\}_{i=1,\dots,m}} \sum_{i=1}^{m} \|\mathbf{x}_i - \mathbf{D}\mathbf{a}_i\|_2^2 + \lambda \|\mathbf{a}_i\|_1 . \tag{2}$$

The optimization is an iterative two-step process: Sparse coding with fixed $\mathbf{D}$ and the dictionary update with fixed $\mathbf{a}$.

3. METHODOLOGY

We first preprocess MR images for noise removal and intensity normalization. Image patches of a predefined size are then extracted using brain mask and are normalized. With the help of training data and manual segmentation images, the image patches are labeled as either lesion or healthy. The dictionaries are learned for each class and the classification of image patches in the test data set is obtained. The final segmentation image is obtained using majority voting.

3.1. Preprocessing

The set of MR images used in this study includes T1-weighted MPRAGE, T2-weighted, PD-weighted and T2-weighted FLAIR with 4-6 time-points for each patient. The provided preprocessed MR images still contain MR artifacts.

We removed such artifacts using non-local means based denoising [6]. These images also have large intensity variations across various modalities and time-points. In order to reduce such intensity variations, each subject-timepoint data volume is rescaled in the intensity range 0-255 and longitudinal intensity normalization is applied to all images [7]. We limit our further analysis to the brain region.

3.2. Patch Labeling

In this step, the intra-cranial MR volume is divided into multiple 3-D image patches of a predefined size. The extracted patches for all MR modalities are then flattened and concatenated together. Keeping the computational complexity of further analysis in mind, we extract a patch every 2 voxels in each direction. Next, the patches corresponding to training data are labeled as belonging to either healthy or lesion class using lesion segmentation masks obtained from two raters and a predefined threshold T_L that defines the number of lesion voxels in a given patch. These patches are finally normalized to limit their individual norms below or equal to unity.

3.3. Patch Classification using Dictionary Learning

Using training data, we learn class specific dictionaries $\mathbf{D}^c$, for the healthy ($c = 1$) and lesion ($c = 2$) classes. The dictionaries learned in this manner consist of a set of basis signals which are better suited to represent the corresponding class data. The decomposition of the test patch using other class dictionary would give rise to a higher representation error.

Given a test patch $\mathbf{y_i}$, the patch classification is performed in two steps: In the first step, the sparse coefficients $\mathbf{a}_i^c$ are obtained using Eq (1) for each class c. The test patch is then assigned to class k such that

$$k = \underset{c}{\operatorname{argmin}} \|\mathbf{y_i} - \mathbf{D}^c \mathbf{a}_i^c\|_2^2 . \tag{3}$$

The dictionaries learned for each class are aimed at better representation of an individual class. However, if there exists differences in the data-complexity between classes, the relative under- or over-representation of either class will lead to worse classification. Now, since the healthy class data represents complex anatomical structures such as white matter (WM), grey matter (GM) and cerebrospinal fluid (CSF), it is associated with more variability as compared to the lesion class. To account for more variability, we allow larger dictionary size for the healthy class and study its effect on MS lesion segmentation.

3.4. Voxel-wise classification

As already stated, we classify patches centered around every 2 voxels in each direction. For voxel-wise classification, we assign each voxel to either of the classes by using majority voting. The voxel is assigned to a particular class using majority votes of all patches which contain that voxel.

4. EXPERIMENTS

We implemented our method using MATLAB. The software SPArse Modeling Software (SPAMS) was used for dictionary learning and sparse coding [8].

For labeling patches, we used threshold $T_L = 15$, as mentioned in Section 3.2. The experiments performed on 5 training subjects using Leave-One-Subject-Out-Cross-Validation yielded the optimal patch size of $5 \times 5 \times 5$, the sparsity parameter of $\lambda = 0.95$ and the dictionary size of 5000 for the healthy class data. The size of the lesion class dictionary varied from 700 to 2500 depending on the total lesion load.

5. CONCLUSION

We proposed MS lesion segmentation technique based on dictionary learning and sparse representations for longitudinal MR data. Learning class specific dictionaries of different sizes not only allows to represent each class data but also avoids relative under- or over-representation of either class data. To further improve the results, it would be interesting to derive dictionaries specific to WM, GM and CSF, instead of learning single dictionary for healthy brain tissues.

6. REFERENCES

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