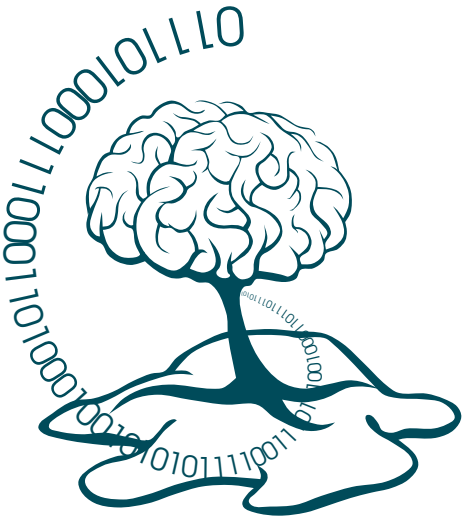

Ischemic Stroke Lesion Segmentation

www.isles-challenge.org

Proceedings

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Preface

Stroke is the second most frequent cause of death and a major cause of disability in industrial countries. In patients who survive, stroke is generally associated with high socioeconomic costs due to persistent disability. Its most frequent manifestation is the ischemic stroke, whose diagnosis often involves the acquisition of brain magnetic resonance (MR) scans to assess the stroke lesion's presence, location, extent, evolution and other factors. An automated method to locate, segment and quantify the lesion area would support clinicians and researchers alike, rendering their findings more robust and reproducible.

New methods for stroke segmentation are regularly proposed. But, more often than desirable, it is difficult to compare their fitness, as the reported results are obtained on private datasets. Challenges aim to overcome these shortcomings by providing (1) a public dataset that reflects the diversity of the problem and (2) a platform for a fair and direct comparison of methods with suitable evaluation measures. Thus, the scientific progress is promoted.

With ISLES, we provide such a challenge covering ischemic stroke lesion segmentation in multi-spectral MRI data. The task is backed by a well established clinical and research motivation and a large number of already existing methods. Each team may participate in either one or both of two sub-tasks:

SISS Automatic segmentation of ischemic stroke lesion volumes from multi-spectral MRI sequences acquired in the sub-acute stroke development stage.

SPES Automatic segmentation of acute ischemic stroke lesion volumes from multi-spectral MRI sequences for stroke outcome prediction.

The participants downloaded a set of training cases with associated expert segmentations of the stroke lesions to train and evaluate their approach, then submitted a short paper describing their method. After reviewing by the organizers, a total of 17 articles were accepted and compiled into this volume. At the day of the challenge, each teams' results as obtained on an independent test set of cases will be revealed and a ranking of methods established.

For the final ranking and more information, visit WWW.ISLES-CHALLENGE.ORG.

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Segmentation of Ischemic Stroke Lesions Using Dictionary Learning

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Abstract. The segmentation of sub-acute ischemic stroke lesions in the brain is a challenging task, typically with laborious manual or semi-automatic methods performed by practiced clinicians. Thus, the search for an automatic segmentation process versatile enough to be widely used clinically continues. Furthermore, automatic multimodal magnetic resonance imaging (MRI) segmentation would improve results by allowing us to use information provided by several different imaging modalities. Here, we propose a supervised learning model using dictionary learning, sparse coding, and support vector machines on several MR sequences: DWI, FLAIR, T1 and T2. We

1 Introduction

A stroke is characterized by restricted blood flow to the brain, depriving brain tissue of vital oxygen and nutrients and resulting in cell death. In developed countries, stroke is the second most frequent cause of death and a major cause of disability. There are two main types of stroke: ischemic, due to lack of blood flow, and hemorrhagic, due to bleeding. Ischemic stroke, caused by interruption of the blood supply to the brain, is much more common than hemorrhagic stroke. Magnetic resonance imaging (MRI), due to its sensitivity and specificity in depicting alterations in brain water content, is often used for diagnosis to detect and assess the stroke lesion presence [7][9][10]. An automatic method to segment the stroke lesions from multimodal MRI would have great clinical use.

2 Materials and Methods

Our approach can be divided into several different sections. The first section consists of preprocessing, which includes image patch extraction and patch normalization. The second section consists of dicionary learning and sparse coding using these image patches [1]. The third section focuses on the relative reconstruction error map based on our learned dictionary. The last section section shows how we use support vector machines on our dictionary coefficients to segment the lesions.

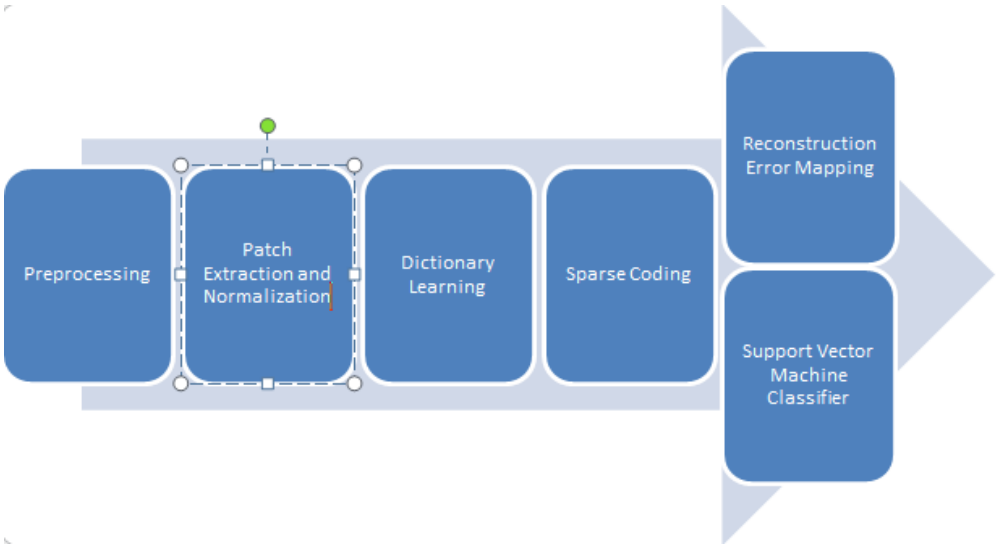

Fig. 1. Flowchart of our proposed ischemic stroke lesion segmentation method. The final step can be either through thresholding of the reconstruction error map or through support vector machine classification on the dictionary coefficients for the image patches.

2.1 Preprocessing

The training data, comprised of T1, T2, FLAIR, and DWI sequences, has already been skull-stripped and co-registered to the FLAIR images. For each MR modality, we extract m image patches from inside the brain and realign them as one-dimensional vectors $x_1, ...x_m \in R^k$, where we choose $k = 27$ for a three-dimensional image patch of size $3 \times 3 \times 3$. For patch normalization, we divide each patch by the value of the highest L_1 norm of all the patches. We then concatenate the corresponding vectors from the different image sequences (T1, T2, FLAIR, and DWI) and re-normalize so that $\|x_i\|_2^2 \leq 1$ and $x_i \in R^{zk}$, where z is the number of image sequences. For experiments here, image patches are divided into training and test sets, and experiments are performed using leave-one-out cross-validation.

2.2 Dictionary Learning and Sparse Coding

Using the image patches as the training set, we search for a dictionary basis $D \in C = \left\{D \in R^{k \times l} s.t. \forall j : \|x_i\|_2^2 \leq 1\right\}$, with l atoms d_j, so that we solve the optimization problem

$$\min_D \sum_{i=1}^{m} \frac{1}{2} \|x_i - D\alpha_i\|_2^2 \; s.t. \; \|\alpha_i\|_1 \leq \lambda_1. \tag{1}$$

We can use one, two, or several dictionaries, based on the number of classes we want (for example, healthy versus lesion patches). The simplest case is with a single dictionary, learned from both the healthy and lesion class patches. This is the method we will describe here; in the future, we can adapt to multi-class dictionaries. For a single dictionary, the number of lesion patches is very small compared to the number of healthy patches, so this dictionary is mainly representative of the healthy brain image patches. The basis D for this dictionary satisfies $x_i \approx D\alpha_i$ for most image patches.

The equation in (1) is a sparse coding problem, where the L_1 constraint and the λ_1 sparsity induced regularizer ensures that only a few atoms of dictionary D will be used to represent an image patch. Studies have shown that this balances the trade-off between sparsity of the coefficients α_i and the reconstruction error. We reconstruct the image patches in the following step

$$\min_{\alpha_1} \|x_i - D\alpha_i\|_2^2 \; s.t. \; \|\alpha_i\|_1 \leq \lambda_2. \tag{2}$$

and obtain a reconstruction error for each image patch based on the λ_2 constraint. Compared to the healthy tissue intensities, the lesions are outliers, so the reconstruction error for those patches would be higher than those for the healthy tissue patches [15].

2.3 Reconstruction Error

For each test patch, we calculate the sparse coefficients α_i given the sparsity constraint λ_2. The relative reconstruction error of each patch is given as

$$err\left(x_i, \alpha_i\right) = \frac{\|x_i - D\alpha_i\|_2}{\|x_i\|_2}. \tag{3}$$

We can map the reconstruction error at the position of the centered voxel within each patch, and the result is an error map throughout the whole brain. We then chose a threshold, for which the test patches with reconstruction error larger than the threshold are classified as lesion patches [6][13].

2.4 Support Vector Machine

Beyond thresholding the reconstruction error, we can take our method a step further. Given our trained overcomplete dictionary, we can further use supervised learning classification techniques on dictionary coefficients to obtain a better segmentation. Here, we take our coefficients α_i and input them as feature vectors into the support vector machine (SVM) framework. From our training set, we have our input feature vector α_i and corresponding target $y_i \in -1, +1$, where is $y_i = +1$ is for lesion tissue and $y_i = -1$ is for healthy tissue. In the feature space, the SVM models are of the form

$$\mathbf{y}\left(\alpha\right) = \omega^{\mathbf{T}}\phi(\mathbf{x}) + \mathbf{b} \tag{4}$$

where the $\phi()$ maps the input vector into higher dimensional feature space, $\mathbf{b}$ is the bias, and ω is the weight vector. A separating hyperplane, generalized to the nonlinear case, that separates the data into healthy and lesion patches can be described as

$$\omega^{\mathbf{T}}\phi(\mathbf{x_i}) + \mathbf{b} \geq +\mathbf{1} \quad \text{if } y_i = +1$$
$$\omega^{\mathbf{T}}\phi(\mathbf{x_i}) + \mathbf{b} \leq -\mathbf{1} \quad \text{if } y_i = -1$$

We want to find, out of all the possible separating hyperplanes, the one with maximum margin $\frac{2}{\|\mathbf{w}\|}$ between the two classes. This hyperplane will separate our healthy patches from our lesions patches. After we have trained our SVM classifier on the coefficients α_i from our dictionary $\mathbf{D}$, we can use it on test data. From our reconstructed image patches, instead of thresholding based on reconstruction error, we plug the coefficients into the SVM classifier[5].

2.5 Implementation

Our method is implemented in MATLAB. We also use the SPArse Modeling Software (SPAMS) [3] from Inria and OMP-Box [2] toolbox from Technion. Many values have been tested using parameter sweeps, and we have found that a good image patch size is $3 \times 3 \times 3$. After testing dictionary sizes ranging from 100 to 5000, we found that a dictionary size $l = 1000$ atoms produced the best results. Empirical results for parameter values showed that sparsity constraints of $\lambda_1 = 0.7$ and $\lambda_2 = 0.85$ tended to work best.

3 Discussion and Conclusion

We proposed an automatic segmentation method for ischemic stroke lesions using dictionary learning on multimodal MRI. Our method uses a single dictionary on all the modalities treated equally, but in the future, we can extend to two dictionaries, one for the lesion class and one for the healthy class of image patches, or even more dictionaries, one each for the white matter, gray matter, and cerebrospinal fluid. We can adapt the size of each dictionary based on the complexity of each class [6].

We can also better utilize the DWI sequence, with its wealth of information about water diffusion directionality and magnitude. We can calculate tensors from the DW images and use invariants such as fractional anisotropy and mean diffusivity to include in our image patches. We can include diffusion directionality information such as principal eigenvectors or eigenvalues. These scalar and vector values we can either concatentate in our image patch vectors, or directly concatenate them in our feature vector that we plug into the support vector machines. Furthermore, instead of SVM, we could use other types of classifiers on the dictionary coefficients, such as neural networks or random forests. With better computational power, we could also try to work with larger image patches, which could capture more textural information, and potentially further improve results.

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