Ischemic Stroke Lesion Segmentation

www.isles-challenge.org

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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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Prediction of Ischemic Lesions using Local Image Properties and Random Forests

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1 Methods

1.1 Registration with Symmetric Normalization

Although the images were registered to the FLAIR sequence, some local differences between spatial locations were observed. We therefore re-registered each sequence to the FLAIR image using Symmetric Normalization (SyN) included in the ANTs software.

1.2 Inhomogeneity Correction

Although, there may be non-uniform image intensities spatially in the brain, we did not perform inhomogeneity correction, for example, the N4 bias correction available within ANTs. We believer that as some lesions may be very large, using inhomogeneity corrections may induce lesion areas to be similar to non-lesion areas. We use estimated smoothed images in the prediction, which should help correct for some inhomogeneity.

1.3 Intensity Normalization

As MRI are acquired in arbitrary units, we performed an intensity-based normalization. Let $x_{s,v}$ represent the intensity of image sequence s for voxel v. Let $Z_{s,v}$ represent the intensity-normalized data. We subtract an estimated mean (μ_s) and standard deviation (σ_s) for each sequence and normalize the data as follows:

$$Z_{s,v} = \frac{x_{s,v} - \mu_s}{\sigma_s}$$

Estimation of the mean and standard deviation The mean and standard deviation are actually estimated from the trimmed distribution of the data of all voxels within the brain mask. The trimming procedure takes all voxels within the brain mask, removes the upper and lower 20% of the data, and estimates the mean and standard deviation from these intensities. This standardizes voxels to the number of (trimmed) standard deviations above the trimmed mean. The goal of the trimming is to delete high-intensity voxels from the lesion or low-intensity voxels from edema.

1.4 Imaging Predictors

We derived a set of imaging predictors from each scan. We will describe each here with their rationale for use. These features make up the potential set of predictors for image segmentation. Each operation uses the normalized images.

Normalized intensity information The normalized voxel intensity value in z-units was included, as it is the main predictor used in visual inspection; high values are indicative of lesion.

1.5 Flipped Difference Image

As most lesions are only on one side of the brain, we calculated the difference in intensity between a voxel and the voxel on its contralateral side. We obtained this image by first rigidly registering the image to the MNI template to account for any head tilt, then flip the image over the left-right axis, and then take the difference of the flipped image and the original image.

Local Moment Information For each voxel, we extracted a neighborhood, denoted N_v, of all adjacent neighboring voxels in 3 dimensions and the voxel itself. Let $I_{s,v}(k)$ denote the normalized voxel intensity in for voxel neighbor k, where $k = 1, \ldots, 27$. We created the voxel neighborhood mean intensity ($\bar{x}_{s,v}$):

$$\bar{x}_{s,v} = \frac{1}{N_v} \sum_{k \in N_v} x_{s,v} \tag{1}$$

We calculated the voxel neighborhood standard deviation (SD), skew, and kurtosis using the following method of moments estimators:

$$\text{SD}_{s,v} = \sqrt{\frac{1}{N_v} \sum_{k \in N(v)} (x_k(v) - \bar{x}(v))^2}$$

$$\text{Skew}(v) = \frac{\frac{1}{N_v} \sum_{k \in N_v} (x_k(v) - \bar{x}(v))^3}{\left[\frac{1}{N_v} \sum_{k \in N_v} (x_k(v) - \bar{x}(v))^2 \right]^{3/2}}$$

$$\text{Kurtosis}(v) = \frac{\frac{1}{N_v} \sum_{k \in N_v} (x_k(v) - \bar{x}(v))^4}{\left(\frac{1}{N_v} \sum_{k \in N_v} (x_k(v) - \bar{x}(v))^2 \right)^2}$$

We acknowledge that we did not divide by $N_v - 1$ for standard deviation and skewness, nor did we subtract by 3 for kurtosis. As N_v should be the same per

voxel, this should not affect the estimates for prediction and will be accounted for in any generalized linear model in the estimated coefficient. We also estimated the local gradient of the normalized intensity for each voxel neighborhood $\nabla_{v,s}$:

$$\nabla_{v,s} = \sqrt{\nabla_{v,s,x}^2 + \nabla_{v,s,y}^2 + \nabla_{v,s,z}^2}$$

Voxels higher in their local mean correspond to voxels adjacent to higher HU voxels on average, which are are more likely to be lesion. The higher order moments can provide information about how homogeneous the intensities in the neighborhood are and where edges occur.

Global Head Information We created 3 images which were obtained by smoothing the original image using large Gaussian kernels ($\sigma = 5mm^3, 10mm^3, 20mm^3$), which can capture any potential homogeneity throughout the scan.

1.6 Model

To train an algorithm, we used 9 images and downsampled $300,000$ voxels. We then used a random forest on these to predict lesion, using 500 trees. From the random forest, we obtained the probability of lesion and determined the threshold for these probabilities using the out-of-sample voxels from the training images, optimizing for the Dice Similarity Index (DSI). We then predicted lesions on the test dataset of 19 scans.

2 Discussion

We believe that our our method allows for a robust procedure for segmentation of large ischemic lesions. This is due to intensity normalization and the set of features that can differentiate lesion areas from healthy tissue. Using local properties, we can leverage spatial information of the image. As such, we can use methods that can use the voxel information without having a more complicated multi-variate framework. The random forest allows for a flexible framework for prediction, especially as some features are highly correlated.