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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Random forests with selected features for stroke lesion segmentation

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Abstract. From clinical practise as well as research methods rises the need for accurate, reproducible and reliable segmentation of ischemic stroke lesions from brain MR scans. This article details a contribution to the Sub-acute Ischemic Stroke Lesion Segmentation (SISS) sub-task of the Ischemic Stroke Lesion Segmentations Challenge (ISLES), organized in conjunction with the MICCAI 2015. The proposed method bases on previous works, which showed the approach to handle various stroke appearances well and to be applicable to potentially flawed data acquired in clinical routine. The method is described in detail and all chosen parameter values are disclosed. Preliminary results on the training data places the approach among the highest ranking contributions.

Keywords: ischemic stroke, lesion segmentation, magnetic resonance imaging, brain MRI, random forest, RDF

1 Introduction

Ischemic stroke is caused by an obstruction of the blood supply to the brain and the subsequent death of brain tissue. Its diagnosis often involves the acquisition of brain magnetic resonance (MR) scans to assess the strokes presence, location, extent, evolution and other factors. An automated method to locate, segment and quantify the lesion area could support the clinicians and render their findings more robust and reproducible. Another demand for automatic stroke lesion segmentation comes from neuroscientists, who employ a research method termed lesion to symptom mapping, which is used to detect correlations between brain areas and cognitive functions by means of negative samples [4]. A number of methods for stroke lesion segmentation have been proposed over the years [2, 8, 12, 3, 13], but none proofed satisfactory to date [11]. The ISLES 2015 challenge offers the first platform for researchers to compare their methods directly and fairly. Our contribution has been previously published [7] and showed good results. It is based on carefully selected features extracted from the MR sequences and used to train a random forest (RF).

2 Method

The challenge's training data consists of multi-spectral (T1, T2, Flair, DWI) scans of 28 patients displaying sub-acute ischemic stroke. A highly diverse range of stroke types is supplied, ranging from large, single-hemisphere MCA to small, embolic cerebellum strokes. Other complexities are non-stroke white matter lesions, midline shifts, ventricular enhancement and the presence of haemorrhages. For training, the manual segmentations of a single expert rater has been provided. For the testing data, two distinct ground truth will be supplied. More details on the data can be found on www.isles-challenge.org.

2.1 Pre-processing

The image data is provided with a 1 mm isotropic resolution, already co-registered and skull-stripped. Nevertheless, the training cases of the challenge display high intensity differences, a normal occurrence for MRI, where intensity ranges are not standardized. With a learning based intensity standardization method implemented in MedPy [6] and based on [9] we harmonize each sequences intensity profile after a prior bias-correction step with CMTK [5].

2.2 Forest classifier

We employ the RF classifier implemented in [10], which is similar to the propositions made by [1]. The classification of brain lesions in MRI is a complex task with high levels of noise [7], hence a sufficiently large number of trees must be trained.

2.3 Features

The primary distinction criteria for identifying pathological tissue of stroke lesions is the MR intensity in the different sequences. The bulk of our voxel-wise features therefore bases on the intensity values.

intensity First feature is the voxel's intensity value.

gaussian Due to the often low signal-to-noise ratio in MR scans and intensity inhomogeneities of the tissue types, we furthermore regard each voxel's value after a smoothing of the volume with a 3D Gaussian kernel at three sizes: $\sigma = 3, 5, 7\ mm$.

hemispheric difference While stroke can affect both hemispheres, it usually does not display symmetric properties. Therefore, we extract the hemispheric difference (in intensities) after a Gaussian smoothing of $\sigma = 1, 3, 5 mm$ to account for noise. Here, the central line of the saggital view is taken as sufficiently close approximation of the sagittal midline.

local histogram Another employed feature is the local histogram, as proposed in [7], which provides information about the intensity distribution in a small neighbourhood around each voxel. The neighbourhoods considered were $R = 5^3, 10^3, 15^3\ mm$, the histogram was fixed to 11 bins.

center distance Finally, we extract the distance to the image center (assumed here to coincide roughly with the brain's center of mass) in mm as final feature. Note that this is not intensity based, but rather discloses each voxel's rough location inside the brain.

All features are extracted from each of the MR sequence, hence in total we obtain 163 values per multi-spectral voxel. Note that all of these features are implemented in MedPy [6].

2.4 Post-processing

After thresholding the a-posteriori class probability maps for a crisp segmentation, all unconnected components with a size smaller than 1000 ml are removed under the assumption that they represent outliers. In all remaining binary components possibly existing holes are closed and a binary dilation of size 1 mm applied to compensate for the methods tendency to under-segment the stroke lesions slightly.

3 Experiments

3.1 Training choices and parameter values

For training our RF, we sample 1,000,000 voxels randomly from all training cases. The ratios between classes in each case are kept intact (i.e. stroke class samples will be highly under-represented). A total of 50 trees are trained for the forest. As split criteria the Gini impurity is employed, a maximum of $\sqrt{163}$ features is considered at each node. No growth restrictions are imposed. The a-posteriori class probabilities produced by the forest are thresholded at a value of 0.4, to counter a slight under-segmentation.

3.2 Preliminary results

Online evaluation is provided with the Dice's coefficient (DC), the average symmteric surface distance (ASSD) and the Hausdorff distance (HD) as quality metrics. Using a leave-one-out evaluation scheme, we have obtained the scores presented in Tab. 1.

Table 1. Mean evaluation results and standard deviation on 28 training cases. See the text for details on the abbreviations employed.

	DC	ASSD	HD
28 cases	0.58 ± 0.29	7.91 ± 13.09	34 ± 29

4 Discussion and conclusion

The favourable placement of our proposed method among the contributions confirms the suitability of our approach for stroke lesion segmentation as has already been observed in [7].

By employing RFs, we have a powerful classifier at our hand that is robust against uninformative features, generalized well and produces good results for a wide range of parameters. Mixing widely used with specially designed features, we can successfully learn to discriminate between ischemic stroke lesion and other, not only healthy, tissue.

On the downside, RFs suffer from the same drawbacks as all other machine learning based methods: The training set must be carefully chosen and types of cases not present in the training data can not be processed.

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