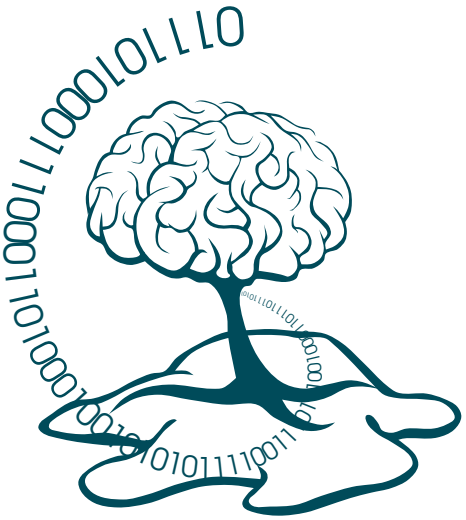

Ischemic Stroke Lesion Segmentation

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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Segmentation of Stroke Lesions in Multi-spectral MR Images Using Bias Correction Embedded FCM and Three Phase Level Set

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Abstract. **Keywords:** lesion segmentation; bias correction; Fuzzy C-Means; level set

1 Introduction

Ischemic stroke is the third leading cause of death in industrialized countries [8]. Due to its excellent soft tissue contrast, magnetic resonance imaging (MRI) has become to be the modality of choice for clinical evaluation of ischemic stroke lesions [4]. As ischemic stroke lesions usually change over time and secondary and remote changes may occur, it is therefore necessary characterizing the tissue changes with different acquisition parameters to produce images of the same physical space in distinctive spectral signatures [1].

In clinical practice, Diffusion weighted images (DWI), T1-weighted (T1W), T2-weighted (T2W) and fluid attenuated inversion recovery (FLAIR) images are often acquired to monitor progression of strokes [7]. In acute stage, hyperintense signal observed on DWI provides important information about the anatomical location and extent of the infarcted territory. In more chronic phase, T2W and FLAIR images are normally used to delineate the final lesion volume. Chronic ischemic lesions appear as hyperintense regions in FLAIR with some heterogeneity within the lesion volume due to ongoing gliosis and demyelination [6].

Early and accurate diagnosis of brain lesion by multi-spectral magnetic resonance images is the key for implementing successful therapy and treatment planning [5]. However, the diagnosis is a very challenging task and can only be performed by professional neuro-radiologists. Lesion segmentation can improve this situation and help radiologists diagnose and make treatment plan. However, due to the variety of the possible shapes, locations, and intensity inhomogeneity, accurate segmentation is still a challenging task [2]. Manual segmentation can be

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performed by trained radiologists, but it is a tedious and time consuming task and is non-reproducible [4].

In this paper, we propose a automatic ischemic stroke lesion segmentation algorithm in multi-spectral images (DWI, T1-w, T2-w, and FLAIR) using bias correction embedded FCM and three phase level set method. The rest of this paper is organized as follows.

2 Method

Before performing lesion segmentation, the input images of different modalities are first rigidly registered in the same coordinate system. Non-brain tissues are then removed from the images. Lesion segmentation is finally carried out with two major steps: 1) preliminary classification of normal brain tissues and lesions in multi-spectral MR images using an improved FCM with the capability of dealing with intensity inhomogeneities, and 2) boundary refinement of preliminary classification using a three phase level set designed for multiple spectral images. More details will be given in the following subsections.

2.1 Image Model

Given an observed MR brain image I defined on a continuous domain $\Omega \subset R^2$, its inhomogeneous intensities can be viewed as a product of the true image J and the bias field b, i.e,

$$I(\mathbf{x}) = b(\mathbf{x})J(\mathbf{x}) + n(\mathbf{x}) \tag{1}$$

where $\mathbf{x} \in \Omega$ and n is zero-mean additive noise. For multi-spectral MR images, we rewrite the above model into the following vector form:

$$\boldsymbol{I}(x) = \boldsymbol{b}(x) \cdot \boldsymbol{J}(x) + \boldsymbol{n}(x) \tag{2}$$

where $\boldsymbol{I}(x) = (I_1(x), I_2(x), \ldots, I_L(x))$, $\boldsymbol{b}(x) = (b_1(x), b_2(x), \ldots, b_L(x))$, $\boldsymbol{J}(x) = (J_1(x), J_2(x), \ldots, J_L(x))$, $\boldsymbol{n}(x) = (n_1(x), n_2(x), \ldots, n_L(x))$, $\cdot$ is the multiplication operator of corresponding components of two vectors, and L is the total channel number.

2.2 Preliminary Segmentation of Lesions and Normal Tissues

For each image channel, true image characterizes an intrinsic physical property of human brain, which ideally takes a specific intensity for each type of tissue (CSF,WM,GM) and lesions and is therefore assumed to be piecewise constant. That is to say, the true image J_i of the i-th channel approximately takes distinct constant values c_{i1}, c_{i2}, ..., and c_{iN} for $N-1$ tissues and lesions in disjoint regions Ω_1, Ω_2, ..., and Ω_N, i.e. $J_i(\mathbf{x}) \approx c_{ij}$ for $\mathbf{x} \in \Omega_j$. Then, in view of the image model in Eq. (2), we have

$$I_i(\mathbf{x}) \approx b_i(\mathbf{x})c_{ij} \quad \text{for} \quad \mathbf{x} \in \Omega_{\mathrm{j}}. \tag{3}$$

Therefore, intensities in the set $I_{ij} = \{I_i(\mathbf{x}) : \mathbf{x} \in \Omega_j\}$ form a cluster with the cluster centroid $m_{ij} \approx b_i(\mathbf{x})c_{ij}$. This clustering property indicates that intensities in the image domain Ω can be classified into N clusters with centroids $m_{i1} \approx b_i(\mathbf{x})c_{i1}$, $m_{i2} \approx b_i(\mathbf{x})c_{i2}$, ..., and $m_{iN} \approx b_i(\mathbf{x})c_{iN}$, respectively. To classify these intensities, we define

$$\mathcal{F}_i = \int_\Omega \sum_{j=1}^{N} \lambda_j \parallel I_i(\mathbf{x}) - b_i(\mathbf{x})c_{ij} \parallel^2 u_j^q(\mathbf{x})d\mathbf{x}. \tag{4}$$

where is any real number that is not less than 1, λ_1, λ_2, ..., λ_N positive weighting coefficients for the N clusters, and $u_j(\mathbf{x})$ is the membership function that indicates whether pixel $\mathbf{x}$ belongs to the j-th tissue or not.

For the multi-spectral MR images, we define

$$\mathcal{F} = \sum_{i=1}^{L} \gamma_i \mathcal{F}_i = \sum_{i=1}^{L} \gamma_i \int_\Omega \sum_{j=1}^{N} \lambda_j \parallel I_i(\mathbf{x}) - b_i(\mathbf{x})c_{ij} \parallel^2 u_j^q(\mathbf{x})d\mathbf{x}. \tag{5}$$

where γ_i are positive weighting coefficient for the i-th spectral image. This objective function is minimized when high membership values are assigned to pixels, intensities of which are close to the centroid, and low membership values are assigned when the pixels are far from the centroids under the condition $\sum_{j=1}^{N} u_j(\mathbf{x}) = 1$ where $u_j(\mathbf{x}) \in [0, 1]$.

Energy minimization of $\mathcal{F}$ can be achieved by alternately minimizing it with respect to each of its variables. For fixed $b_i(\mathbf{x})$ and $u_j(\mathbf{x})$, $i = 1, 2, ..., L$, and $j = 1, 2, ..., N$, we minimize $\mathcal{F}$ with respect to c_{ij} by resolving $\frac{\partial \mathcal{F}}{\partial c_{ij}} = 0$. It is obvious that $\mathcal{F}$ is minimized at $c_{ij} = \hat{c}_{ij}$, given by

$$\hat{c}_{ij} = \frac{\int_\Omega b_i(\mathbf{x}) I_i(\mathbf{x}) u_j^q(\mathbf{x})}{\int_\Omega b_i^2(\mathbf{x}) u_j^q(\mathbf{x})} \tag{6}$$

For fixed $u_j(\mathbf{x})$ and c_{ij}, $i = 1, 2, ..., L$, and $j = 1, 2, ..., N$, we minimize $\mathcal{F}$ with respect to $b_i(\mathbf{x})$ by resolving $\frac{\partial \mathcal{F}}{\partial b_i(\mathbf{x})} = 0$. It can be shown that $\mathcal{F}$ is minimized at $b_i(\mathbf{x}) = \hat{b}_i(\mathbf{x})$, given by

$$\hat{b}_i(\mathbf{x}) = \frac{I_i(\mathbf{x}) \sum_{j=1}^{N} \lambda_j c_{i,j} u_j^q(\mathbf{x})}{\sum_{j=1}^{N} \lambda_j c_{i,j}^2 u_j^q(\mathbf{x})} \tag{7}$$

For the case $q > 1$, minimization of $\mathcal{F}$ with respect to $u_j(\mathbf{x})$ can be implemented by resolving the following Lagrangian equation:

$$\sum_{i=1}^{L} \gamma_i \int_\Omega \sum_{j=1}^{N} \lambda_j \parallel I_i(\mathbf{x}) - b_i(\mathbf{x})c_{ij} \parallel^2 u_j^q(\mathbf{x})d\mathbf{x} - \lambda \left(\sum_{j=1}^{N} u_j(\mathbf{x}) - 1 \right) = 0 \tag{8}$$

where λ is the Lagrangian multiplier and $\sum_{j=1}^{N} u_j(\mathbf{x}) = 1$ is the extremum condition. For fixed $b_i(\mathbf{x})$ and c_{ij}, $i = 1, 2, ..., L$, and $j = 1, 2, ..., N$, we take

partial derivative of the above equation with respect $u_j(\mathbf{x})$, set the result to 0, and resolve the equations with the constraint that $\sum_{j=1}^{N} u_j(\mathbf{x}) = 1$. Then, it can be shown that $\mathcal{F}$ is minimized at $u_j(\mathbf{x}) = \hat{u}_j(\mathbf{x})$, given by

$$\hat{u}_j(\mathbf{x}) = \frac{\left(\lambda_j \sum_{i=1}^{L} \gamma_i \| I_i(\mathbf{x}) - b_i(\mathbf{x}) c_{i,j} \|^2\right)^{\frac{1}{1-q}}}{\sum_{k=1}^{N} \left(\lambda_k \sum_{i=1}^{N} \gamma_i \| I_i(\mathbf{x}) - b_i(\mathbf{x}) c_{i,k} \|^2\right)^{\frac{1}{1-q}}} \tag{9}$$

Preliminary segmentation of CSF, WM, GM and stroke lesions is performed in this step in an iterative process.

2.3 Lesions Segmentation Using a Three Phase Level Set Method

To refine boundaries of the preliminary segmentation, we propose a three phase level set formulation as the second step of the proposed method in this subsection. The proposed level set formulation can be seen as a extension of the local intensity clustering (LIC) model with the capability of dealing with intensity inhomogeneities [3]. Preliminary segmentation results are used to initialize the level set function, such that the zero level contour of the initial level set function is near the true lesion boundaries.

Consider a relatively small circular neighborhood with a radius ρ centered at a given point $\mathbf{y} \in \Omega$, defined by $\mathcal{O}_{\mathbf{y}} \triangleq \{\mathbf{x} :\mid \mathbf{x} - \mathbf{y} \mid \leq \rho\}$. For each image channel, the bias field in the neighborhood can be ignored due to its slowly and smoothly varying property. Taking into account the constant intensity c_{ij} of the true image J in Ω_j, we obtain

$$b_i(\mathbf{x}) J_i(\mathbf{x}) \approx b_i(\mathbf{y}) c_{ij} \quad \text{for} \quad \mathbf{x} \in \Omega_{\mathrm{j}} \cap \mathcal{O}_{\mathbf{y}}. \tag{10}$$

This local intensity clustering property allows us to apply the standard K-means algorithm in the following continuous form to classify these local inhomogeneous intensities in the neighborhood $\mathcal{O}_{\mathbf{y}}$. Therefore, taking all the L channel images into account, we define

$$\mathcal{E}_y = \sum_{j=1}^{N} \lambda_j \int_{O_y} \left(\sum_{i=1}^{L} \chi_i \| I_i(\mathbf{x}) - b_i(\mathbf{y}) c_{ij} \|^2 \right) u_j(\mathbf{x}) d\mathbf{x} \tag{11}$$

where λ_j is the weighting coefficient used to control size of j-th tissue, χ_i is the weighting coefficient for the i-th channel, and u_j is the membership function of Ω_j. On account of the inherent property of the membership function u_j in representing the subregion Ω_j, $\mathcal{E}_{\mathbf{y}}$ can be rewritten as

$$\mathcal{E}_y = \sum_{j=1}^{N} \lambda_j \int_{\Omega_j} K_\sigma(\mathbf{x} - \mathbf{y}) \left(\sum_{i=1}^{L} \chi_i \| I_i(\mathbf{x}) - b_i(\mathbf{y}) c_{ij} \|^2 \right) d\mathbf{x} \tag{12}$$

where K_σ is a nonnegative kernel function with the property $\int_{|\mathbf{u}| \leq \sigma} K_\sigma(\mathbf{u}) = 1$.

To ensure the partition $\{\Omega_j\}_{j=1}^N$ of the entire domain Ω to be the one such that $\mathcal{E}_{\mathbf{y}}$ is minimized for all $\mathbf{y}$ in Ω, we minimize the integral of $\mathcal{E}_{\mathbf{y}}$ with respect to $\mathbf{y}$ over the entire image domain Ω and define

$$\mathcal{E} = \int_{\Omega} \left(\sum_{j=1}^{N} \lambda_j \int_{\Omega_j} K_\sigma(\mathbf{x}-\mathbf{y}) \left(\sum_{i=1}^{L} \chi_i \parallel I_i(\mathbf{x}) - b_i(\mathbf{y}) c_{ij} \parallel^2 \right) d\mathbf{x} \right) d\mathbf{y}. \quad (13)$$

As our goal is to segment lesions, we consider the background and CSF as one region, GM and WM as the second region, and the lesions as the third region. We therefore use $M_1(\phi_1,\phi_2) = (1-H(\phi_1))(1-H(\phi_2))$, $M_1(\phi_1,\phi_2) = H(\phi_1)(1-H(\phi_2))$, and $M_1(\phi_1,\phi_2) = H(\phi_2)$ to represent these regions and rewrite $\mathcal{E}$ as

$$\mathcal{E} = \int_{\Omega} \left(\sum_{j=1}^{N} \lambda_j e_j(\mathbf{x}) M_j(\phi_1(\mathbf{x}),\phi_2(\mathbf{x})) \right) d\mathbf{x} \quad (14)$$

where

$$e_j(\mathbf{x}) = \int_{\Omega} K_\sigma(\mathbf{x}-\mathbf{y}) \left(\sum_{i=1}^{L} \chi_i \parallel I_i(\mathbf{x}) - b_i(\mathbf{y}) c_{ij} \parallel^2 \right) d\mathbf{y} \quad (15)$$

The energy $\mathcal{E}$ defined above is used as the data term of the final energy functional of the proposed level set formulation, which defined by

$$\mathcal{F} = \mathcal{E} + \mathcal{P} + \mathcal{L}. \quad (16)$$

where $\mathcal{P}$ and $\mathcal{L}$ are the regularization term and arc length term defined below to maintain the regularity of the level set functions and smooth the 0-level set contours of the level set functions, respectively.

$$\mathcal{P} = \mu_1 \int \frac{1}{2}(\mid \nabla\phi_1(\mathbf{x}) \mid -1)^2 d\mathbf{x} + \mu_2 \int \frac{1}{2}(\mid \nabla\phi_2(\mathbf{x}) \mid -1)^2 d\mathbf{x} \quad (17)$$

$$\mathcal{L} = \nu_1 \int \mid \nabla H(\phi_1(\mathbf{x})) \mid d\mathbf{x} + \nu_2 \int \mid \nabla H(\phi_2(\mathbf{x})) \mid d\mathbf{x} \quad (18)$$

where μ_1, μ_2, ν_1 and ν_2 are weighting coefficients and H is the Heaviside function.

For fixed b and $\mathbf{c}$, we minimize the final energy functional $\mathcal{F}$ using the standard gradient descent method and obtain

$$\frac{\partial\phi_1}{\partial t} = \delta(\phi_1)(1-H(\phi_2))(\lambda_1 e_1 - \lambda_2 e_2) + \mu_1 \left(\nabla^2\phi_1 - \mathrm{div}\left(\frac{\nabla\phi_1}{\mid \nabla\phi_1 \mid} \right) \right) + \nu_1 \delta(\phi_1) \mathrm{div}\left(\frac{\nabla\phi_1}{\mid \nabla\phi_1 \mid} \right). \quad (19)$$

For fixed ϕ and b, the optimal $\mathbf{c}$ that minimizes the final energy functional $\mathcal{F}$ is given by

$$c_{ij} = \frac{\int I_i(\mathbf{x}) M_j(\phi_1(\mathbf{x}),\phi_2(\mathbf{x}))(b_i * K_\sigma)(\mathbf{x}) d\mathbf{x}}{\int M_j(\phi_1(\mathbf{x}),\phi_2(\mathbf{x}))(b_i^2 * K_\sigma)(\mathbf{x}) d\mathbf{x}}, \quad i = 1,2,...,L \quad \text{and} \quad \mathrm{j} = 1,2,...,\mathrm{N}. \quad (20)$$

For fixed ϕ and $\mathbf{c}$, the optimal b that minimizes the final energy functional $\mathcal{F}$ is given by

$$b_i = \frac{\left(I_i \sum_{j=1}^{N} c_{ij} M_j(\phi_1, \phi_2)\right) * K_\sigma}{\sum_{j=1}^{N} c_{ij}^2 M_j(\phi) * K_\sigma}, \quad i = 1, 2, ..., L. \tag{21}$$

2.4 Implementation

The implementation of the proposed method can be straightforwardly expressed as follows.

• Step 1. Remove non-brain tissues from the images and register them in the same coordinate system.

• Step 2. Preliminary classification of normal brain tissues and lesions. Update each variables of energy function defined in Eq. (5) iteratively until convergence criterion has been reached or the iteration number exceeds a predetermined maximum number.

• Step 3. Initialize the level set functions using preliminary classification results and keep ϕ_2 fixed. Update each variables of energy functional defined in Eq. (16) iteratively until convergence criterion has been reached or the iteration number exceeds a predetermined maximum number.

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