

AUTOMATIC TWO STAGE CLASSIFICATION AND SEGMENTATION OF ISCHEMIC STROKE LESIONS IN DIFFUSION-WEIGHTED MRI

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Target Audience: Clinician research scientists, neuroimaging researchers.

Purpose: Diffusion-weighted imaging (DWI) is the most useful imaging modality for ischemic stroke diagnosis and prognosis in patients seen within 12h of symptom discovery¹. Currently, baseline DWI lesion volume is used as an inclusion or exclusion criterion for clinical trials of acute stroke intervention such as SWIFT Prime² or EXTEND³. Despite the high sensitivity and excellent interrater agreement of DWI for the detection of early ischemic changes (EIC)⁴, the manual assessment of exact DWI lesion volumes is time consuming and therefore impractical in the acute stroke setting. Instead, a more rapid approximation of the extent of the DWI lesion would be preferable. Recently, we demonstrated several strategies of pixel classification for fast segmentation of ischemic lesions in DWI⁵. Although the preliminary results were promising, the specificity remained low due to the large inclusion of false detected regions. In this study, we extend the best pixel classification strategy with a region based classification strategy to remove false detected regions and thereby improve the segmentation performance.

Methods: We retrospectively analyzed MRI from ischemic stroke cases (N=116) for which imaging was done within 12h of last known well, expert manual outlines were available and DWI was positive for ischemic stroke. DWI was acquired using an echo-planar imaging (EPI) sequence on a 1.5T magnet (GE Medical Systems) with diffusion-weighting or b-value=1000 s/mm². Apparent diffusion coefficient (ADC) maps were calculated from DWI and b₀ (b-value=0 s/mm²) images. The b₀ images were used as T2-weighted images (T2WI). Manual lesion outlines were made based on DWI while attempting to limit the outline to areas of reduced ADC. If more than one scan was available for a patient case, only the first scan was considered. The proposed method consists of two sequential stages. In the first stage of the method, DWI and T2WI were corrected for non-uniformities using a non-parametric method⁶ and an exponential ADC (eADC=exp(-b*ADC)) was computed. The eADC, DWI and T2WI images were normalized based on median CSF and brain parenchyma intensity⁵. A Naïve Bayes classifier was then used to segment tissue into normal or lesion classes by using predetermined probability density functions and a-priori probabilities to estimate which class an unknown voxel most likely belongs to.⁶ A lesion map was obtained as voxels for which the probability of classification in the abnormal class was higher than the probability of classification as normal tissue. Finally, post-processing steps were performed to refine the lesion segmentation (iterative hole filling, heuristic removal of isolated outlines near air-tissue boundary and with strong edges). In the second stage of the method, regional analysis was performed on the lesion map obtained from the initial stage. Firstly, lesions were localized by 3-dimensional connected-component labeling which identified isolated regions. Secondly, several attributes were collected from each located lesion (e.g. mean and stdev of eADC, DWI and T2WI, volume, eccentricity, elongation, roundness, centroid, orientation, axis length). Thirdly, the extracted attributes of the candidate regions were summarized into a likelihood of ischemia using a supervised classifier. Finally, candidate regions were removed from the lesion map when they were below a likelihood of 0.5.

Experiments: The following classifiers were trained and examined for their discriminating performance: a Linear Discriminant Analyzer (LDA); a Support Vector Machine (SVM) with a radial kernel; a k-Nearest Neighbour (kNN) classifier; GentleBoost (CB); a RandomForest (RF) classifier; and a generalized linear model (GLM). Selection of features was carried out by a greedy backward-search selection to establish the most discriminant features. Leave-one-patient-out training and testing of the classifier was performed with the area under the Receiver Operating Characteristic (ROC) curve as the criterion to be optimized. The segmentation results of each classifier were evaluated by comparing the binary lesion segmentations with the reference standard on a voxel-wise basis. As a performance measure, the Dice similarity coefficient (DSC)⁸ was used, for which a value of 1 indicates a perfect overlap and a value of 0 means no overlap at all. The results were compared using a two-sided Wilcoxon test and P<0.05 was considered significant.

Results: The median DSC using the initial pixel classification approach was 0.58 (0.19-0.77). All classifiers significantly improved the segmentation performance in the two-stage approach. The segmentation performances using the different classifiers in increasing median DSC order were: kNN 0.675 (0.34-0.82); GLM 0.683 (0.37-0.82); SVM 0.698 (0.39-0.82); ADA 0.700 (0.40-0.82); LDA 0.700 (0.39-0.82); RF 0.700 (0.40-0.82), see Fig 1 for all results.

Discussion: DWI is a reliable and routinely-used modality in the acute setting of ischemic stroke. Automated approaches for outlining the DWI lesion have the potential to assist in the rapid assessment of lesion volumetry in the acute setting of stroke. Our results demonstrate that the segmentation performance of pixel classification approach can be significantly improved with regional analysis, i.e. using a supervised classifier that removes false detected lesion regions from the initial stage. Further research will focus on improving the segmentation results by local segmentation refinement of the correctly localized lesions.

References: [1] Schellinger P. et al, Neurology, 2010; 75:177-185. [2] <http://clinicaltrials.gov/show/NCT01657461>

[3]<http://clinicaltrials.gov/ct2/show/NCT00887328>. [4] Barber PA, et al. Stroke. 1999;30:2059-2065. [5] Mocking S., et al. ISMRM 2011. [6] Ref Sled JG, IEEE TMI. 1998;17(1):87-97. [7] Maron ME, Journal of the ACM 1961; 8(3): 404-417. [8] Dice LR, Ecology, 1945; 26 (3): 297-302.

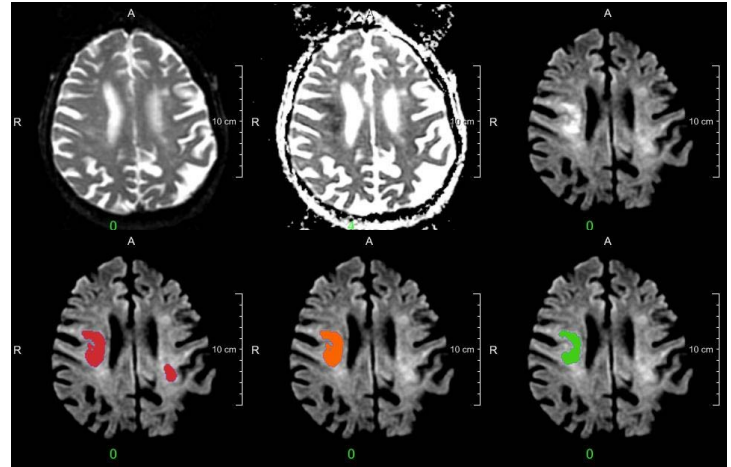


Figure 1: Example case with from (upper) left to right a T2WI, ADC and DWI map used as input for the method. The bottom row shows the DWI with as overlay from left to right the output from the pixel classification (red), two-stage approach (orange) and manual outline (green). Note the false detected lesion in the left hemisphere which was correctly removed by the two-stage approach.

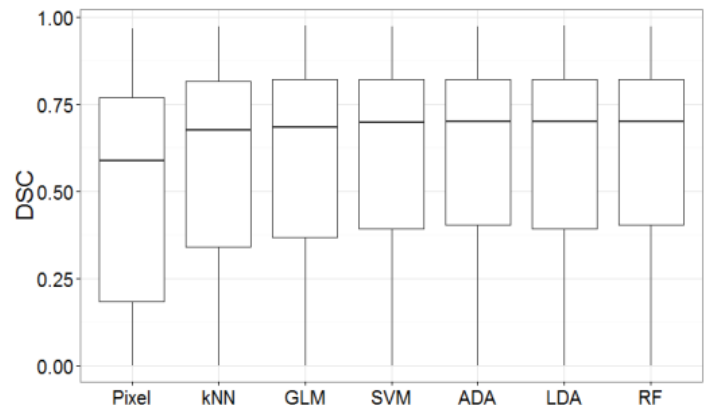


Figure 2: Segmentation performances using the pixel classification and the two-stage strategy using different classifiers. All two-stage approaches are significantly better than the pixel classification.