WAMAS: A Multi-Agent System with Improved Watershed Segmentation for Brain MRI Analysis

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Accurate segmentation of brain magnetic resonance imaging (MRI) scans is vital for early diagnosis and treatment planning of brain tumors. Classical methods such as the Watershed algorithm often suffer from over-segmentation, noise sensitivity, and limited adaptability. To address these issues, we propose a Watershed-based Multi-Agent System (WAMAS) that combines empirical thresholding, statistical similarity measures, and agent-driven negotiation for robust tumor delineation. In preprocessing, edge features are extracted with Canny and Sobel operators, while region descriptors are obtained via Quadtree decomposition and refined through mean–variance analysis to adapt thresholds under noise. During processing, Region Agents propose the proposed local watershed on its appropriate regions where seed candidate merges based on similarity scores, while Edge Agents validate boundaries using gradient consistency; conflicts are resolved through cooperative decision rules to prevent over-segmentation. Evaluations on BrainWeb and IBSR167 datasets under varying noise levels showed that WAMAS outperforms baseline Watershed and advanced methods such as U-Net and B-UNet, and best results obtained are respectively 97.38% accuracy, 96.50% sensitivity, and 96.84% specificity. Paired t-tests ($p < 0.01$) confirmed significant improvements. These results demonstrate that WAMAS provides coherent boundaries and robust performance, making it a promising tool for clinical neuroimaging.

Povzetek:

Table S1: General Attributes of the Segmentation Agent.

Attribute	**Description**
Mean $I(x,y)=\mu$	$$\mu = \frac{1}{N^2}\sum_{i=j=1}^{N}\rho_{i,j}$$
Variance $I(x,y) = \sigma$	$$\sigma = \sum_{i=1}^{N}\sum_{j=1}^{N}(i-\mu)^2\,\rho(i,j)$$
Sum Average	$$\sum_{i=2}^{2N} i\,\rho_{x+y}(i), \quad \rho_{x+y}(k) = \sum_{i=1}^{N}\sum_{j=1}^{N}P(i,j), \quad i+j=k=2,3,\ldots,2N$$
Correlation	$$\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\frac{\big(P(i,j)\,\rho_{i,j}-\mu_x\mu_y\big)}{\sigma_x\sigma_y}$$
Correlation 1	$$\frac{HXY-HXY1}{\max\{HX,HY\}}$$ where $$HXY = -\sum_i\sum_j \rho_{i,j}\,\log_2\rho_{i,j}, \quad HXY1 = -\sum_i\sum_j \rho_{i,j}\,\log_2\{\rho_x(i)\,\rho_y(j)\}$$
Correlation 2	$$HXY2 = -\sum_i\sum_j\{\rho_x(i)\,\rho_y(j)\}\,\log_2\{\rho_x(i)\,\rho_y(j)\}$$ where $$\rho_x(i) = \sum_{j=1}^{N}\rho_{i,j}$$
Energy	$$\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\rho_{i,j}^2$$

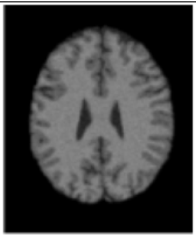
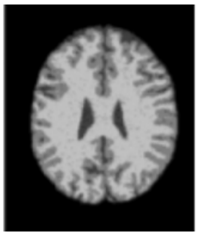
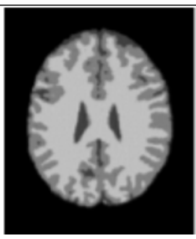
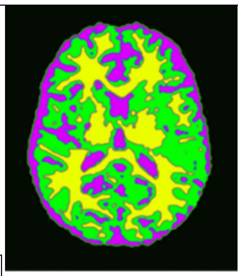
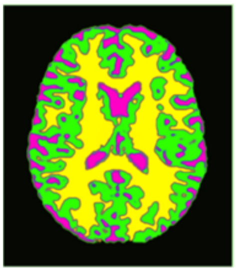
Table S2: Key Attributes of the Edge Agent.

Attribute	Description
Mean $I(x,y) = \mu$	$$\mu = \frac{1}{N^2} \sum_{i=j=1}^{N} \rho_{i,j}$$
Variance $I(x,y) = \sigma$	$$\sigma = \sum_{i} \sum_{j} (i-\mu)^2 \, \rho(i,j)$$
Sum Average	$$\sum_{i=2}^{2N} i \, \rho_{x+y}(i), \quad \rho_{x+y}(k) = \sum_{i=1}^{N} \sum_{j=1}^{N} P(i,j), \quad i+j=k=2,3,\ldots,2N$$
Correlation	$$\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{P(i,j)\,\rho_{i,j} - \mu_x \mu_y}{\sigma_x \sigma_y}$$
Correlation 1	$$\frac{HXY - HXY1}{\max\{HX, HY\}}$$ where $$HXY = -\sum_{i} \sum_{j} \rho_{i,j} \, \log_2 \rho_{i,j}, \quad HXY1 = -\sum_{i} \sum_{j} \rho_{i,j} \, \log_2 \{\rho_x(i)\, \rho_y(j)\}$$
Correlation 2	$$HXY2 = -\sum_{i} \sum_{j} \{\rho_x(i)\, \rho_y(j)\} \, \log_2 \{\rho_x(i)\, \rho_y(j)\}$$ where $$\rho_x(i) = \sum_{j=1}^{N} \rho_{i,j}$$
Energy	$$\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \rho_{i,j}^2$$

Table S3: Key Attributes of the Region Agent.

Attribute	**Description**
Morphology operations	$\oplus$, $\ominus$
dist_transform	> 0
Threshold	$[0.5, 1.5[$
Marker-label	Char label
Border_type	Char label
Border_Value	> 0
Average altitude of a watershed H_a	$$H_a = \frac{\sum(A_{i,i+1}\,(h_i + h_{i+1}))}{2A}$$
$A_{i,i+1}$	area between two consecutive contour lines
$h_i, h_{i+1}, h_{\min}, h_{\max}$	altitudes of contour lines
A	watershed surface
Medium altitude of the watershed H_m	$$H_m = \frac{H_{\max} + H_{\min}}{2}$$
Average slope of the watershed S_a	$$S_a = \frac{D \times L}{A}$$ where D = altitude difference of extreme stream points, L = total length of contour lines.
Longitudinal slope S_l	$$S_l = \frac{\Delta H}{L}$$
Degree of development of the hydrographic network D_d	$$D_d = \frac{\sum L_i}{A}$$
GRE$_i$	Region Graph of Edges
RAM	Region Adjacency Map
NNGSR$_i$	Region Graph Adjacency with Nearest Neighbor Graph for Sub-Region SR_i
Emp_THR	Empirical Threshold

Table S4: Simulated T1-wighted MR image from IBSR 18

Images	**CSF**	**WM**	**GM**
IBSR18			
I1 			
I2 			
I3 			
Final Processing Phase			
WAMAS	R[I1] 	R[I2] 	R[I3]