Thresholding Method Using Ant Colony Optimization Algorithm for Brain MRI Segmentation

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Introduction

The problem

Thresholding is one of the most popular techniques in image segmentation because of its simplicity. However, sometimes, calculating the optimal threshold can be a difficult computational problem, specially in complex images where it can not be directly extracted from the histogram, as in brain MRI images. Thus, [1] proposed an optimized thresholding method based on the ant colony algorithm (ACO) for the segmentation of brain tissues from MRI images.

Ant colony algorithm (ACO)

This algorithm is inspired in the ants behaviour when they are looking for a food source [2].

- Ants deposite pheromone while they travel and, even though initially they move randomly, they tend to choose paths with higher amount of pheromones.
- The concentration of pheromone evaporates with time. However, shorter paths will be more attractive because ants travelling in short paths will come back to their nests with food faster, so there will always be high amounts of fresh pheromone.
- This way, the search area will be focused in paths that lead to high quality food sources, even though there is always a probability of exploring new paths, that can result in discovering alternative short paths.

Theoretical basis of the algorithm

The segmentation method is based on maximizing the between-class variance (objective function) using ACO and textural features (homogeneity) to obtain optimal thresholds for the segmentation of MRI brain images in white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF).

Between-class variance

Otsu et. al defined a method to compute the optimal threshold by maximizing the between-class variance [3].

$$\sigma_B^2 = \omega_0 \cdot \omega_1 \cdot (\mu_1 - \mu_0)^2 \tag{1}$$

Where ω_0 and ω_1 are the probabilities of class occurrence and μ_0 and μ_1 are the mean normalized intensities of each class.
Therefore, the optimal threshold (k^*) is the one that maximizes the objective function:

$$\sigma_B^2(k^*) = \max_{1 \leq k \leq L} \sigma_B^2(k) \tag{2}$$

Where *L* is the number of grey levels of the image and *k* is the threshold. Extending the problem to multithresholding (k_1 and k_2):

$$\sigma_B^2(k_1^*, k_2^*) = \max_{1 \leq k_1 < k_2 \leq L} \sigma_B^2(k_1, k_2) \tag{3}$$

Homogeneity

The homogeneity of a pixel placed in *(i,j)* is calculated using two 3x3 windows:

- w_{ij}: a window centered in *(i,j)*.
- $w_{i_1 j_1}$: a window centered in (i_1, j_1), being (i_1, j_1) one of the eight nearest neighbours of *(i,j)* in different directions (0º, 45º, 90º, 135º, 180º, -45º, -90º or -135º).

$$H = \frac{\sum_{i=1}^{3}\sum_{j=1}^{3}[1 - \frac{|w_{ij} - w_{i_1 j_1}|}{y_{max}}]}{9} \tag{4}$$

Where y_{max} is the maximum gray value difference in the area of the image corresponding to the brain (target area).
Minimum and average homogeneity:

$$H_{min} = min(H_0, H_{45}, H_{90}, H_{135}, H_{180}, H_{-45}, H_{-90}, H_{-135}) \tag{5}$$

$$H_{average} = \frac{\sum(H_0, H_{45}, H_{90}, H_{135}, H_{180}, H_{-45}, H_{-90}, H_{-135})}{8} \tag{6}$$

Initialization

- **Initial solution**: two random grey values of the target area are selected as best-so-far solution (optimal thresholds).
- **Pheromone distribution**:
  - 0 in the pixels out of the target area.
  - In the target area, using a ramp function (highest values in pixels whose intensities are closer to the best-so-far solution).
- **Ant distribution**: only in the target area and, at most, one ant per pixel.

Ant colony algorithm (ACO)

Pseudo-code of the algorithm:

```
while stopping criteria are not reached do
    for each ant do
        repeat
            Move randomly
        until at least one of the 8 nearest neighbours has a different label
        Choose next node applying the transition probability rule (neighbour with highest ρ_ij (7))
        Calculate the fitness value (f_i) using the objective function (between-class variance)
        if f_i > f_best-so-farsolution then
            Update best-so-far solution
        end if
    end for
    Update pheromone levels
end while
```

Transition probability rule

$$\rho_{ij} = \begin{cases} \frac{\tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta}}{\sum \tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta}} & if\ (i,j) \epsilon I \\ 0 & Otherwise \end{cases} \tag{7}$$

Where *I* is the 3x3 window centered in the current ant location, τ is the level of pheromone, η is the homogeneity and α and β define the weight of τ and η in the decision.

Solution construction

Depends of the label of ant's current and next location:

- **GM-WM or GM-CSF**:the intensities of both pixels are selected as a possible threshold between GM-WM or GM-CSF, respectively.
- **WM-CSF**: both intensities are selected as the two thresholds needed for the segmentation.

Post-processing

Based on homogeneity and performed in two steps:

1. If H_{min} of the pixel in *(i,j)* $> T$, the mode of w_{ij} classes is applied to all the pixels in the window whose class label is different.
2. If $H_{average}$ of the pixel in (i,j) $< min(H_{average}) + \omega \cdot min(H_{average})$, the pixel can be a weak edge. If there are more than four pixels in w_{ij} whose intensity difference with the central pixel (i,j) is higher than a threshold, the class of the central pixel (i,j) is changed to the mode of the classes of w_{ij}.

The values of the parameters were optimized and fixed as $T = 0.95$ and $\omega = 0.1$.

Results

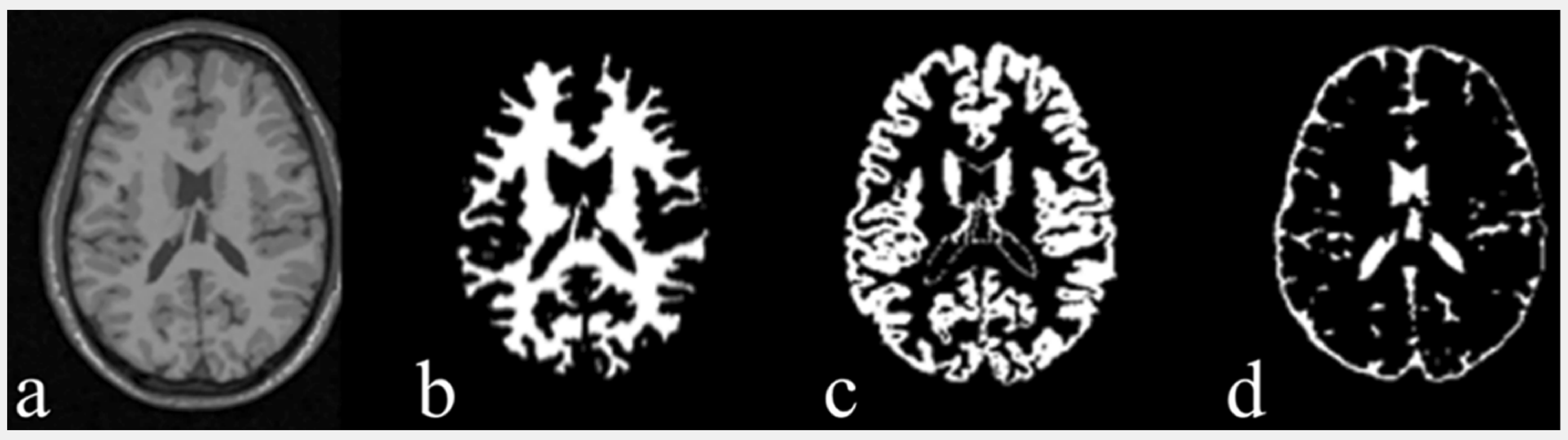

Figure 1. Results of the ACO algorithm: **a** Original image **b** WM **c** GM **d** CSF [1]

In *Table 1*, $F_1 score$ (8) values of the proposed method (ACO) are compared to other methods.

$$F_1 = 2 \cdot \frac{Precision \cdot Sensitivity}{Precision + Sensitivity} \tag{8}$$

Table 1. F_1 score of different algorithms

F_1 score	ACO	ABC	PSO	K-means	EM
GM	0.91727	0.91383	0.91535	0.91089	0.90927
WM	0.94589	0.94295	0.9444	0.94217	0.9401
CSF	0.90377	0.89053	0.89978	0.8984	0.89644

References

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