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Hidden Markov Random Fields and Particle Swarm Combination for Brain Magnetic Resonance Image Segmentation

El-Hachemi Guerrount, Ramdane Mahiou, Samy Ait-Aoudia
ESI - Ecole nationale Supérieure en Informatique, BP 68M, 16270, Oued-Smar, Algiers, Algeria
e_guerrount@esi.dz, r_mahiou@esi.dz, s_ait_aoudia@esi.dz

Abstract: The interpretation of brain images is a crucial task in the practitioners’ diagnosis process. Segmentation is one of key operations to provide a decision support to physicians. There are several methods to perform segmentation. We use Hidden Markov Random Fields (HMRF) for modelling the segmentation problem. This elegant model leads to an optimization problem. Particles Swarm Optimization (PSO) method is used to achieve brain magnetic resonance image segmentation. Setting the parameters of the HMRF-PSO method is a task in itself. We conduct a study for the choice of parameters that give a good segmentation. The segmentation quality is evaluated on ground-truth images, using the Dice coefficient also called Kappa index. The results show a superiority of the HMRF-PSO method, compared to methods such as Classical MRF and MRF using variants of ACO (Ant Colony Optimization).

Keywords: Brain image segmentation, Hidden Markov Random Field, Swarm Particles Optimization, Dice coefficient.

1. Introduction

With the overwhelming number of medical images, the manual analysis and interpretation of images from different imaging modalities (Radiography, MRI - Magnetic Resonance Imaging, CT - Computed tomography, etc) became a tedious task. This fact underlines the necessity of automatic image analysis, through several operations including segmentation.

Hidden Markov Random Field (HMRF) provides an elegant way to model the segmentation problem. Since the seminal paper of Geman and Geman [12], Markov Random Fields (MRF) models for image segmentation have been extensively investigated [3,15,32,34]. The segmentation process consists in finding the hidden information namely the segmented image by observing the data from the original image. We seek the segmented image, according to the MAP (Maximum A Posteriori) criterion [30]. MAP estimation leads to the minimization of energy function [8]. This problem is computationally intractable. Therefore, optimization techniques are used to compute a solution.

Particle Swarm Optimization (PSO) has emerged as one of the best optimization techniques. This new class of metaheuristics was proposed in 1995 by Eberhart and Kennedy [10]. This technique was extensively studied by many researches [18,28]. The selection of PSO parameters, in the algorithm simulation, is a problem in itself [6,10,11,15]. A bad choice of parameters can lead to a chaotic behaviour of the optimization algorithm.

In this paper we investigate parameters setting and performance of Hidden Markov Random Field (HMRF) and Particle Swarm Optimization (PSO) combination named HMRF-PSO [2,15] in brain MR (Magnetic Resonance) images segmentation. In this specific case, segmentation consists in partitioning the brain image into different characteristic parts that are gray matter, white matter and cerebrospinal fluid. The segmentation evaluation is conducted on ground-truth images from Brainweb1 and IBSR2 databases. The Dice coefficient is used to assess the quality of the segmentation. The HMRF-PSO method is compared to methods using Markov Random Field and variants of Ant Colony Optimization [32]. The achieved results are promising and show a clear superiority of the HMRF-PSO method.

This paper is organized as follows. An overview of previous work is given in section 2. In section 3, we give The Hidden Markov Random Field model principles in the context of image segmentation. The Particle Swarm Optimization and HMRF combination is explained in section 4. Experimental results on medical samples are given in section 5. Section 6 concludes the paper.

2. Previous work

Brain MRI images segmentation has attracted a particular focus in medical imaging. The importance of this modality has favoured the abundance of research on automatic extraction of image characteristics resulting from medical examinations. The segmentation techniques can be classified in four broad categories: Threshold-based techniques, Region-based techniques, Classification techniques and Model-based techniques [13].
Threshold-based techniques [23,27] use image histogram and find one or more intensity thresholds to identify the different classes of the image. In the case of foreground/background separation, one threshold is identified. If the image contains n distinctive classes (n-1) thresholds are necessary. The threshold-based techniques are very noise sensitive.

Region based techniques explore the pixels of the image and assemble them in non overlapping regions according to a criterion of homogeneity. In this context, several authors used region growing [25] or watersheds to perform segmentation [14,26].

In classification techniques, pixels are grouped based on the some properties of these pixels (grey levels, texture or colour). The groups formed are called clusters. C-means based techniques [1,33] and Markov Random Fields are part of the classification-based methods and are widely used for brain segmentation.

In model-based segmentation, as in deformable models and level sets, a model is built for a specific anatomic structure by incorporating a priori information concerning this structure (shape, location, and orientation) [17,22].

The presence of noise in the acquired images can severely degrade the segmentation results and thus makes the process of segmentation useless. Denoising is generally performed prior to the effective segmentation [4,5,16,21,24,29,31].

3. Hidden Markov Random Field (HMRF)

An image is formed of a finite set S of sites corresponding to the pixels, \( S = \{s_1, s_2, \ldots, s_M\} \) of \( M=n^m \) sites. The sites in S are related by neighbourhood system \( V(S) \).

The image to segment into K classes or the observed image, \( y = (y_1, \ldots, y_M) \) is seen by the Hidden Markov Random Field model as a realization of a family of random variables defined on S, \( Y = (Y_1, \ldots, Y_M) \). Each random variables \( \{Y_s\}_{s \in S} \) takes its values in the space \( \Lambda_{obs} = \{0..255\} \). The configuration set is \( \Omega_{obs} \).

The segmented image, \( x = (x_1, \ldots, x_M) \) is seen as the realization of another Markov Random Field, \( X = (X_1, \ldots, X_M) \), defined on the same lattice \( S \), takes its values in the discrete space \( \Lambda = \{1,2,\ldots,K\} \). \( K \) represents the number of classes or homogeneous regions in the image. The configuration set is \( \Omega \).

The Hidden Markov Random Filed provides an elegant way to model the segmentation problem by using the MAP (Maximum A Posteriori) estimator. This latter consists in finding a realization \( x \) of \( X \) by observing the data of the realization \( y \), representing the image to segment (The figure 1 shows an example for \( K=4 \)).

Computing the exact segmentation \( x^* = \arg \min_{x \in \Omega} \{ \Psi(x,y) \} \) of the image \( y \) is impossible but we can seek an approximation \( \hat{x} = (\hat{x}_1, \ldots, \hat{x}_M) \) of the exact segmentation \( x^* = (x^*_1, \ldots, x^*_M) \) using optimization techniques.

Our way to look for an approximation \( \hat{x} \) is to seek an approximation \( \mu^* = (\hat{\mu}_1, \ldots, \hat{\mu}_j, \ldots, \hat{\mu}_K) \) of \( \mu^* = (\mu_1^*, \ldots, \mu_j^*, \ldots, \mu_K^*) \) where \( \mu_j^* \) is the mean of the class \( j \) in \( x^* \) and \( \hat{\mu}_j \) is the mean of the class \( j \) in \( \hat{x} \).

The segmented image \( x \) is calculated after computation of \( \mu \) by classifying \( y_s \) into the nearest mean \( \mu_j \) of \( \mu \) (i.e. \( y_s = j \)) if the nearest of \( y_s \) is \( \mu_j \).

Our goal becomes looking for \( \mu^* \) instead \( x^* \) such that \( \mu^* = \arg \min_{\mu \in \Lambda} \{ \Psi(\mu,y) \} \) where:

\[
\Psi(\mu,y) = \begin{cases} 
\sum_{j=1}^{K} f(\mu_j, y) & \text{if } \mu \in [0..255]^K \\
\infty & \text{else} 
\end{cases}
\]

\[
f(\mu_j, y) = \sum_{s \in S} \left[ \ln(\sigma_j) + \frac{(y_s - \mu_j)^2}{2\sigma_j^2} \right] + \frac{\beta}{T} \sum_{s \in S} (1-2\delta(x, y_s))
\]

The aim of the MAP estimator is to maximize the probability \( P(X=x|Y=y) \) which is equivalent in this context to minimize the function \( \Psi(x,y) \) [2,15].

Figure 1. Observed and hidden image.
$S_j$ contains all the sites $s$ such that the nearest mean to $y_s$ is $\mu_j$. $\sigma_j$ is the standard deviation in which:

$$\sigma_j = \sqrt{\frac{1}{M} \sum_{s \in S_j} (y_s - \mu_j)^2}$$

4. HMRF and Particle Swarm Optimization combination (HMRF-PSO)

Formally, each particle $i$ has a position (a solution) $m_i(t) = (m_{i1}(t),...,m_{iK}(t))$ and a velocity $v_i(t) = (v_{i1},...,v_{iK})$ at the time $t$.

Each particle $i$ at the time $t$ compute its own segmented image $x_i(t) = (x_{i1}(t),...,x_{iM}(t))$ using its position $m_i(t)$ where $x_{ij}(t) = j$ if the nearest mean to $y_j$ is $m_{ij}(t)$.

Each particle $i$ at the time $t$ measure its position $m_i(t)$ which equal to $\Psi(m_i(t), y)$.

Let $m_i(t) = (m_{i1}(t),...,m_{iK}(t))$ the best position visited by the particle $i$ till the time $t$ (we called it the local best), so:

$$m_i(t+1) = \begin{cases} m_i(t) & \text{if } \Psi(m_i(t), y) \leq \Psi(m_i(t+1), y) \\ m_i(t+1) & \text{if } \Psi(m_i(t), y) > \Psi(m_i(t+1), y) \end{cases}$$

Let $\mu(t) = (\mu_1(t),...,\mu_K(t))$ the best position visited by all the particles till the time $t$ (we called it the global best), so:

$$\mu(t) \in \{m_1(t),...,m_1(t),...,m_{NP}(t)\}$$

Where NP is the number of particles

$$\mu(t) = \arg \min_{m_i(t)} \{\Psi(m_i(t), y),...\Psi(m_{NP}(t), y)\}$$

The velocity $v_i(t+1)$ of the particle $i$ at the time $t+1$ is influenced by its local best $m_i(t)$ and the global best $\mu(t)$, as follow:

$$v_i(t+1) = w* v_i(t) + L_i(t) + G_i(t)$$

$$L_i(t) = c_1 * r_{ij}(t) * (m_i(t) - m_{ij}(t))$$

$$G_i(t) = c_2 * r_{ij}(t) * (\mu(t) - m_{ij}(t))$$

Where $w$ is called the inertia weight, $c_1$ and $c_2$ are the acceleration constants; $r_{ij}(t)$ and $r_{ij}(t)$ are random variables between 0 and 1. The velocity $v_{ij}$ is limited by $V_{max}$ to ensure convergence.

The position $m_i(t+1)$ of the particle $i$ is changed at time $t+1$ by the velocity $v_i(t+1)$ using the following formula:

$$m_i(t+1) = m_i(t) + v_i(t+1)$$

When the maximal number of iterations is reached, we take the global best as the solution $\hat{\mu} = \mu$

5. Experimental Results

5.1. Parameters Setting

Evaluating the quality of the segmentation using the Dice Coefficient [9] can only be made where the a priori segmentation is known. The matching between the class $C_i$ in the segmentation image and its ground truth $C_i^*$ is given by the following formula:

$$DC = \frac{C_i^* \cap C_i}{C_i^* \cup C_i} = \frac{2TP}{2TP + FP + FN}$$

TP is the true positive; FP is the false positive and FN is the false negative.

5.1.1 HMRF parameters

Choosing the appropriate parameters for HMRF-PSO combination method is a delicate task. A bad choice can lead to poor results. We will focus in this section on setting the parameters of HMRF process.

Figure 3 shows an IRM scan and its corresponding segmentations in four classes with $\beta=1, T_0=4$ and varying the parameter $\tau$. 

![Figure 3. IRM scan and its corresponding segmentations.](image-url)
Figure 3. Segmentation varying $\tau$.

Figure 4 shows an image and its corresponding segmentations in two classes with $\beta=1$, $\tau=0.98$ and varying the parameter $T_0$.

<table>
<thead>
<tr>
<th>$T_0$</th>
<th>Segmentation</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td><img src="image1" alt="Segmentation image" /></td>
</tr>
<tr>
<td>4</td>
<td><img src="image2" alt="Segmentation image" /></td>
</tr>
<tr>
<td>1</td>
<td><img src="image3" alt="Segmentation image" /></td>
</tr>
</tbody>
</table>

Figure 4. Segmentation varying $T_0$.

Figure 5 shows an image and its corresponding segmentations in two classes with $\tau=0.98$, $T_0=4$ varying the parameter $\beta$.

<table>
<thead>
<tr>
<th>$\beta$</th>
<th>Segmentation</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td><img src="image4" alt="Segmentation image" /></td>
</tr>
<tr>
<td>1</td>
<td><img src="image5" alt="Segmentation image" /></td>
</tr>
<tr>
<td>2</td>
<td><img src="image6" alt="Segmentation image" /></td>
</tr>
</tbody>
</table>

Figure 5. Segmentation varying $\beta$.

5.1.2 PSO parameters

To select the correct settings for PSO algorithm, we have performed a statistical analysis on brain images segmentation differentiating between Grey Matter (GM), White Matter (WM) and Cerebro-Spinal Fluid (CSF) classes. An overview of the results is given below.

The number of iterations is a parameter that has a very important role in convergence and terminates the optimization process. Figure 6 shows the influence of the change in the number of iterations on the segmentation quality. Other process parameters have been set at: $c1=0.7$, $c2=0.9$, $w=0.7$, $vmax=5$, $swarm\_size =30$ and $\beta=1$.

![Figure 6. Iteration number variation.](image7)

Figure 6. Iteration number variation.

Figure 7 shows the swarm velocity influence on the quality of the segmentation. Other process parameters have been set at: $c1=0.4$, $c2=0.4$, $w=0.4$, $iteration\_number=100$, $swarm\_size =40$ and $\beta=1$. $Vmax$ speed must be limited to avoid the algorithm performance degradation. Beyond a certain speed, the segmentation quality deteriorates.

![Figure 7. Maximum velocity variation.](image8)

Figure 7. Maximum velocity variation.

The size of the swarm plays a very important role in the optimization process. This parameter affects robustness and quality of the result. Figure 8 shows the influence of the change of the swarm size on the quality segmentation. Other process parameters have been set at: $c1=0.6$, $c2=0.7$, $w=0.6$, $vmax=5$, $iteration\_number=100$ and $\beta=1$.

![Figure 8. Particle number variation.](image9)

Figure 8. Particle number variation.

5.2. Comparative study

To assess the HMRF-PSO combination method, we made a comparative study with four segmentation algorithms operating on brain images that are Classical MRF, MRF-ACO (Ant Colony Optimization), MRF-ACO-Gossiping [32] and LGMM [19].
To perform a meaningful comparison, we use the brain medical images with their ground truth from IBSR database and Brainweb database with Modality=T1 and Slice thickness=1mm. The comparison will be based on the Dice coefficient.

Brainweb [7] images are simulated MRI volumes for normal brain from McGill University. These simulations are based on an anatomical model of normal brain. In this database, an image can be selected by setting modality, slice thickness, noise and intensity non-uniformity.

The Internet Brain Segmentation Repository (IBSR) provides manually-guided expert segmented brain data. This repository is made available to the scientific community by the Neuroimaging Informatics Tools and Resources Clearinghouse (NITRC) [20]. Its aim is to encourage the evaluation and development of segmentation methods.

The parameters setting for the four methods used in the study are summarized in table 1.

<table>
<thead>
<tr>
<th>Method</th>
<th>N</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classical MRF</td>
<td>1</td>
<td>T: Temperature=4, a: Pheromone info. Influence=1, b: Heuristic info. Influence=1, q: Evaporation rate=0.1, w: Pheromone decay coefficient=0.1</td>
</tr>
<tr>
<td>MRF-ACO</td>
<td>2</td>
<td>T: Temperature=4, a: Pheromone info. Influence=1, b: Heuristic info. Influence=1, q: Evaporation rate=0.1, w: Pheromone decay coefficient=0.1, c1: Pheromone reinforcement coefficient=10, c2: Pheromone reinforcement coefficient=0.1</td>
</tr>
<tr>
<td>MRF-ACO-Gossiping</td>
<td>3</td>
<td>T: Temperature=4, a: Pheromone info. Influence=1, b: Heuristic info. Influence=1, q: Evaporation rate=0.1, w: Pheromone decay coefficient=0.1, c1: Pheromone reinforcement coefficient=10, c2: Pheromone reinforcement coefficient=0.1</td>
</tr>
<tr>
<td>HMRF-PSO</td>
<td>4</td>
<td>T: Temperature=4, t=0.98, c1=0.6, c2=0.7, w=0.6, vmax=5, swarm_size=70, iteration_number=100</td>
</tr>
</tbody>
</table>

Table 2 shows the mean values of Dice coefficient for Brainweb database. The slices, used form Brainweb database are: 85, 88, 90, 95, 97, 100, 104, 106, 110, 121 and 130.

<table>
<thead>
<tr>
<th>The method</th>
<th>GM</th>
<th>WM</th>
<th>CSF</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classical-MRF</td>
<td>0.75</td>
<td>0.72</td>
<td>0.78</td>
<td>0.75</td>
</tr>
<tr>
<td>MRF-ACO</td>
<td>0.72</td>
<td>0.76</td>
<td>0.78</td>
<td>0.75</td>
</tr>
<tr>
<td>MRF-ACO-Gossiping</td>
<td>0.72</td>
<td>0.76</td>
<td>0.78</td>
<td>0.75</td>
</tr>
<tr>
<td>HMRF-PSO</td>
<td>0.95</td>
<td>0.98</td>
<td>0.93</td>
<td>0.95</td>
</tr>
</tbody>
</table>

The table 3 shows the mean values of Dice coefficient for IBSR database. The slices, used from 1-24(IBSR database), are: 18, 20, 24, 26, 30, 32 and 34.

<table>
<thead>
<tr>
<th>The method</th>
<th>GM</th>
<th>WM</th>
<th>CSF</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classical-MRF</td>
<td>0.76</td>
<td>0.82</td>
<td>0.24</td>
<td>0.61</td>
</tr>
<tr>
<td>MRF-ACO</td>
<td>0.77</td>
<td>0.82</td>
<td>0.25</td>
<td>0.61</td>
</tr>
<tr>
<td>MRF-ACO-Gossiping</td>
<td>0.77</td>
<td>0.82</td>
<td>0.25</td>
<td>0.61</td>
</tr>
<tr>
<td>HMRF-PSO</td>
<td>0.83</td>
<td>0.85</td>
<td>0.31</td>
<td>0.66</td>
</tr>
</tbody>
</table>

The results clearly show the prevalence of the HMRF-PSO method compared with other methods.

Table 4 shows the comparison between HMRF-PSO with The parameters: c1=0.45, c2=0.8, w=0.45 and LGMM method [19]. We have used the Brainweb databases with different noise levels. The slices used are 85, 88, 90, 95, 97, 100, 104, 106 and 110. The first column (N,I) gives the noise and the intensity non-uniformity.

<table>
<thead>
<tr>
<th>(N,I)</th>
<th>GM</th>
<th>WM</th>
<th>CSF</th>
<th>Mean</th>
<th>GM</th>
<th>WM</th>
<th>CSF</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>0%</td>
<td>0.69</td>
<td>0.66</td>
<td>0.75</td>
<td>0.70</td>
<td>0.95</td>
<td>0.98</td>
<td>0.95</td>
<td>0.96</td>
</tr>
<tr>
<td>15%</td>
<td>0.90</td>
<td>0.94</td>
<td>0.89</td>
<td>0.91</td>
<td>0.94</td>
<td>0.96</td>
<td>0.94</td>
<td>0.95</td>
</tr>
<tr>
<td>30%</td>
<td>0.91</td>
<td>0.95</td>
<td>0.88</td>
<td>0.91</td>
<td>0.91</td>
<td>0.95</td>
<td>0.92</td>
<td>0.93</td>
</tr>
<tr>
<td>45%</td>
<td>0.90</td>
<td>0.95</td>
<td>0.87</td>
<td>0.91</td>
<td>0.88</td>
<td>0.93</td>
<td>0.89</td>
<td>0.90</td>
</tr>
<tr>
<td>60%</td>
<td>0.19</td>
<td>0.74</td>
<td>0.73</td>
<td>0.56</td>
<td>0.81</td>
<td>0.90</td>
<td>0.78</td>
<td>0.83</td>
</tr>
</tbody>
</table>

The HMRF-PSO combination globally outperforms LGMM method [19].

6. Conclusion

In this paper, we have presented a method referred to as HMRF-PSO that combines Hidden Markov Random Fields and Particle Swarm Optimization to perform segmentation. A statistical study was also carried out to set the parameters of the method. The tests conducted have focused on the brain images from the largely used databases, Brainweb and IBSR.

The HMRF-PSO combination outperforms other combination methods tested that are: Classical MRF, MRF-ACO-Gossiping and MRF-ACO methods. Therefore, the proposed method has the potential to be used in computer aided medical diagnosis Systems. Nonetheless, the proposed method has to be tested on images coming from other modalities. A comparative study with other segmentation methods must also be conducted to confirm the method supremacy.

On the other hand, direct search techniques, specifically Nelder-Mead and Torczon methods, are currently under investigation to solve the optimisation problem.

References


