Medical Image Segmentation using Particle Swarm Optimization

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***Abstract*. Segmentation of medical images is one of the fundamental problems in image processing field. It aims to provide a crucial decision support to physicians. There are several methods to perform segmentation. Hidden Markov Random Fields (HMRF) constitutes an elegant way to model the problem of segmentation. This modelling leads to the minimization of an energy function. In this paper we focus on Particles Swarm Optimization (PSO) method to solve this optimization problem. The quality of segmentation is evaluated on grounds truths images using the Kappa index. The results show the supremacy of the HMRF-PSO method compared to K-means and threshold based techniques.**

Keywords. Medical image segmentation; Hidden Markov Random Field; Swarm Particles Optimization; Kappa Index.

I. INTRODUCTION

Image segmentation is one of the fundamental problems in the medical field. The principal aim is to aid the practitioner to interpret images produced by various modalities exams. More specifically, in image segmentation, a label is assigned to each pixel in an image such that pixels having the same label share some common characteristics. There are several techniques to solve the segmentation problem. We can classify these methods in six broad classes that are: edge detection based methods, clustering methods, threshold based methods, Markov random fields methods, Region growing and deformable models. Among these methods, Hidden Markov Random Field (HMRF) provides an elegant way to model the segmentation problem. HMRF Model and Gibbs distributions provide powerful tools for image modelling [13,15,16]. A labeling is searched according to the MAP (Maximum A Posteriori) criterion [22]. The modelling leads to the minimization of an energy function [5,18,23]. Optimizations techniques are used to compute a solution.

In this paper we will focus on the combination of HMRF and Particle Swarm Optimization (PSO). PSO optimization technique is a new class of metaheuristics proposed in 1995 by Kennedy and Eberhart [7]. This technique was investigated by many other researches [2,9,14,17,20]. This algorithm is inspired by the social behaviour of animals moving in swarms as flocking bird or schooling fish. The performance of the swarm is greater than the sum of the performance of its parts.

The quality of segmentation is evaluated on ground truth images using an objective criterion that is the Kappa index (also called Dice coefficient). The achieved results are satisfactory and show a superiority of the HMRF-PSO method compared to K-means and threshold based techniques.

This paper is organized as follows. In section 2, we provide some concepts of Markov Random Field model. Section 3 is devoted to Hidden Markov Field model and its use in image segmentation. In section 4, we explain the Particle Swarm Optimization technique. We give in section 5 experimental results on sample images with ground truth. Section 6 is devoted to conclusions.

II. MARKOV RANDOM FIELD MODEL

A. *Neighbourhood system and cliques*

Image pixels are represented as a lattice denoted S of M=n*m sites. $S=\{s_1,s_2,\ldots,s_M\}$ The sites or pixels in *S*, as shown in figure1, are related by a neighbourhood system *V(S)* satisfying:

$$\forall\, s \in S,\, s \notin V_s(S), \forall \{s,t\} \in S,\, s \in V_t(S) \Leftrightarrow t \in V_s(S) \qquad (1)$$

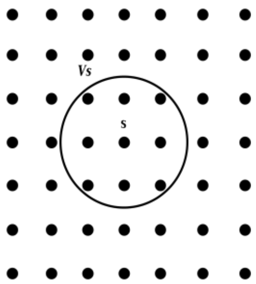


Figure 1. Spatial context in natural images

The relationship V(S) represents a neighbourhood tie between sites. An r-order neighbourhood system denoted $V^r(S)$ is defined by:

$V^r s(S)=\{t \in S \mid distance(s,t)^2 \leq r^2, s \neq t\}$ (2) (2.2)

A clique *c* is a subassembly of sites with regard to a neighbourhood system. The clique *c* is a singleton or all the different sites of *c* are neighbours. If *c* is not a singleton, then:

$\forall \{s,t\} \in c,\ t \in Vs(S)$ (3)

B. Markov Random Field

Let $X=\{X_1,X_2,\ldots,X_M\}$ be a family of random variables on the lattice *S*. Each random variable taking values in the discrete space $\Lambda=\{1,2,\ldots,K\}$. The family *X* is a random field with configuration set $\Omega = \Lambda^M$. A random field *X* is said to be an MRF on S with respect to a neighbourhood system *V(S)* if and only if:

$\forall\ x \in \Omega,\ P(x) > 0$ (4)

$\forall s \in S, \forall x \in \Omega, P(X_s=x_s/X_t=x_t, t \neq s)=P(X_s=x_s/X_t=x_t, t \in V_s(S))$ (5)

The Hammersley-Clifford theorem establishes the equivalence between Gibbs fields and Markov fields. The Gibbs distribution is characterized by the following relation:

$$P(x)= Z^1\, e{-}\frac{U(x)}{T} \qquad (6)$$

$$Z=\sum_{y \in \Omega} e{-}\frac{U(y)}{T} \qquad (7)$$

T is a control parameter well known as temperature; *Z* is a normalization constant referred to the partition function. *U(x)* is the energy function of the Gibbs field defined as:

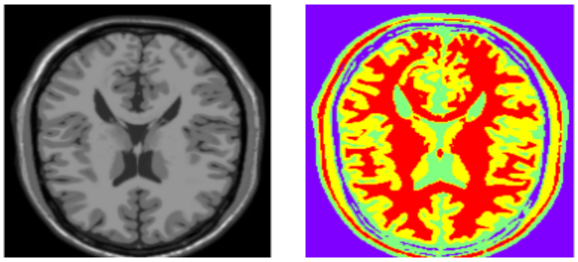
$$U(x)=\sum_{c \in C} U_c(x) \qquad (8)$$

U(x) is defined as a sum of potentials over all the possible cliques *C*.

III. Hidden Markov Random Field model

A strong model for image segmentation is to see the image to segment as a realization of a Markov Random Field $Y=\{Ys\}s \in S$ defined on the lattice S. The random variables $\{Ys\}s \in S$ have gray level values in the space $\Lambda obs=\{0..255\}$. The configuration set is Ω obs.

The segmented image is seen as the realization of another Markov Random Field X defined on the same lattice S, taking values in the discrete space $\Lambda=\{1,2,\ldots,K\}$ where K represents the number of classes or homogeneous regions in the image.



Y: Observed Image X: Hidden Image

Figure 2. Observed and hidden image.

In the context of image segmentation we have a problem with incomplete data. To every site $i \in S$ is associated different information: observed information expressed by the random variable Y_i and missed or hidden information expressed by the random variable X_i. The Random Field X is said Hidden Markov Random Field. The segmentation process consists in finding a realization x of X by observing the data of the realization y representing the image to segment. Figure 2 shows a grey level magnetic resonance image and the corresponding segmented image in four classes (grey matter, white matter, cerebrospinal fluid and the background).

In summary, we seek a labelling $\hat{x}$ which is an estimate of the true labeling x^*, according to the MAP (Maximum A Posteriori) criterion (maximizing the probability $P(X=x|Y=y)$) or equivalently by minimizing the function $\Psi(x,y)$.

$$\hat{x} = \arg\min_{x \in X} \{\Psi(\mathrm{x}, \mathrm{y})\} \quad (9)$$

$$\Psi(\mathrm{x}, \mathrm{y}) = \sum_{s \in S} \frac{(\mathrm{y}_s - \mu_{x_s})^2}{2\sigma_{x_s}^2} + \ln(\sqrt{2\pi}\sigma_{x_s}) - \frac{\beta}{T} \sum_{\mathrm{s}, t \in \mathrm{C}_2} (1 - 2\delta(x_s, x_t)) \quad (10)$$

IV. PSO - Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a powerful optimization method inspired by the social behaviour animals living or moving in swarm like bird flocking or fish schooling. The idea is that a group of unintelligent individuals may have a complex global organization. This optimization method is based on the collaboration between individuals. An individual of the swarm is only aware of the position and speed of its nearest neighbours. Each particle adjusts its behaviour based on its experience and the experience of its neighbours to build a solution to a problem. Through simple displacement rules (in the solution space), the particles can gradually converge towards the solution of the problem.

Formally, each particle i has a position $x_i(t)$ at the time t in the space of possible solutions which change at time $t+1$ by a velocity $v_i(t)$. The velocity $v_i(t)$ is influenced by the best position $y_i(t)$ visited by itself (i.e. its own experience) and $\mathrm{z_i(t)}$ the best position visited by all particles (we called it global best). The positions are measured by a fitness function f which depends on the optimization problem and K the space dimension.

$$x_i(t) = (x_{i1}, x_{i2}, \ldots, x_{ij}, \ldots, x_{iK}) \quad (11)$$
$$v_i(t) = (v_{i1}, v_{i2}, \ldots, v_{ij}, \ldots, v_{iK}) \quad (12)$$
$$y_i(t) = (y_{i1}, y_{i2}, \ldots, y_{ij}, \ldots, y_{iK}) \quad (13)$$
$$z(t) = (z_1, z_2, \ldots, z_j, \ldots, z_K) \quad (14)$$

y_i is updated over time according to the following formula:

$$\mathrm{y_i(t+1)} = \begin{cases} \mathrm{y_i(t)} \ \text{if } \mathrm{f(x_i(t+1)) \geq f(y_i(t))} \\ \mathrm{x_i(t+1)} \ \text{if } \mathrm{f(x_i(t+1)) < f(y_i(t))} \end{cases} \quad (15)$$

The best position visited by all the particles till the time t, $\mathrm{z(t)}$ will be calculated at time t with the following formula:

$$\mathrm{z(t)} \in (\mathrm{y_1(t), y_2(t), \ldots, y_s(t)}) = \min\{\mathrm{f(y_1(t)), f(y_2(t)), \ldots, f(y_s(t))}\} \quad (16)$$

where s denotes number of particles (the size of the swarm).
The velocity $v_i(t) = (v_{i1}(t), v_{i2}(t), \ldots, v_{ij}(t), \ldots, v_{iK}(t))$ of the particle i at the time t is updated using the following formula:

$$\mathrm{v_{ij}(t+1) = w^*v_{ij}(t) + c1^*r_{1j}^*\left(y_{ij}(t) - x_{ij}(t)\right) + c2^*r_{2j}^*\left(z_j(t) - x_{ij}(t)\right)} \quad (17)$$

w is called the inertia weight; $c1$ and $c2$ are the acceleration constants; r_{1j} and r_{2j} are random variables between 0 and 1; velocity v_{ij} is limited by Vmax to ensure convergence.

The position x_i of the particle i is updated using the following formula:

$$x_i(t+1)=x_i(t)+v_i(t+1) \quad (18)$$

The PSO algorithm is summarized hereafter:

PSO Algorithm:

Initialization
For every particle i $\in$ 1,...,s do
Initialize x_i randomly
Initialize v_i randomly
$y_i = x_i$
End for
Repeat
For every particle i $\in$ 1,...,s do
Evaluate particle i fitness $f(x_i)$
Update y_i using formula (4.1)
Update z using formula (4.2)
For each j $\in$ 1,...,n do
Update velocity using formula (4.3)
End for
Update x_i using formula (4.4)
End for
Until satisfaction of convergence criteria

In the HMRF-PSO combination, we use the PSO algorithm to minimize the formula given by equation (10). Each particle displacement is defined as:

$$x_i(t) = (\mu_{i1}, \mu_{i2}, \dots, \mu_{ij}, \dots, \mu_{iK}) \quad (19)$$

where K represents the number of classes or homogeneous regions in the image and μ_{ij} is j^{th} mean of the particle i^{th} and fitness function $f=\Psi$.

V. Experimental Results

In our experiments we will use five algorithms on medical images [21]. The methods tested are: HMRF-PSO combination, K-means and three threshold-based methods that are Otsu method, Mixture Of Gaussians (MOG), Mixture Of Generalized Gaussians (MOGG). To perform a meaningful comparison, we use medical images with ground truth segmentation. For this purpose, we have used the Brainweb (http://www.bic.mni.mcgill.ca/brainweb/) database [4] largely used in the evaluation of brain segmentation. Three classes are highlighted: Gray Matter (GM), White Matter (WM) and cerebrospinal fluid (CSF).

Evaluating the quality of the segmentation can only be made where the a priori segmentation is known. The Kappa Index KI (also called Dice coefficient) given hereafter measures the quality of the segmentation.

$$KI = 2 \times \frac{TP}{2 \times TP + FP + FN} \quad (20)$$

Where TP stands for True Positive, FN False Negative and FP False Positive.

The Kappa Index equals 1 when the two segmentations are identical and 0 when no classified pixel matches the true segmentation.

We will use in the comparison with threshold based methods the same images given in [3]. The Brainweb slices used are numbered 90-119 from the subject: Modality = T1, Slice thickness = 1mm, Noise = 3% and Intensity non-uniformity = 20%. A MRI scan and its ground truth and HMRF-PSO segmentations are shown in figure 3.

In table1, we give the mean Kappa Indexes obtained by using HMRF-PSO combination (for the parameters: c1=0.3, c2=0.4, w=0.4, vmax=5, swarm_size =80, iteration=100 and B=1), K-means, Otsu method, Mixture Of Gaussians (MOG), Mixture Of Generalized Gaussians (MOGG).

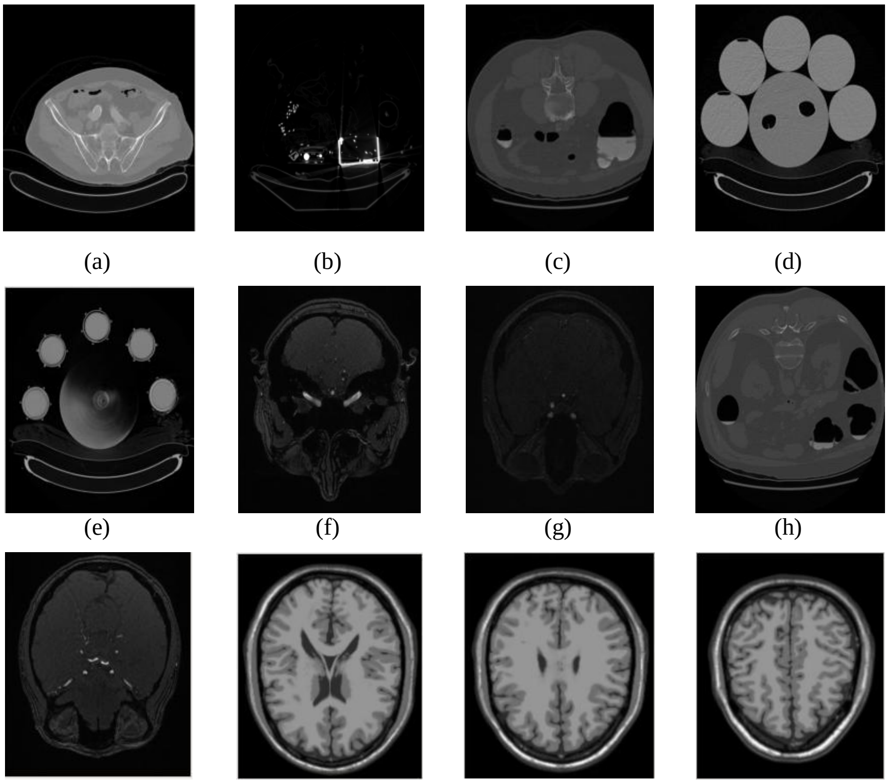
(a) (b) (c)

Figure 3. (a) MRI scan, (b) ground truth segmentation, (c) HMRF-PSO

	GM	WM	CSF
HMRF-PSO	0.84	0.95	0.60
K-means	0,76	0,88	0,49
Otsu	0.71	0.87	0.13
MoG	0.23	0.71	0.19
MoGG	0.82	0.92	0.46

TABLE 1. KAPPA INDEX VALUES.

Ground truth images are not always available. Segmenting real medicals slices can't be evidently evaluated by the use of the Kappa Index. The visual result of the segmented image must be appreciated by specialists to assert a good processing. Hereafter are given some segmentation results (figure 5) of real medical images (figure 4) using HMRF-PSO combination (for the parameters: c1=0.3, c2=0.4, w=0.4, vmax=5, swarm_size=80, iteration=100 and B=1).



(a) (b) (c) (d) (e) (f) (g) (h) (i) (j) (k) (l)

Figure 4. Medical images with no ground truth.

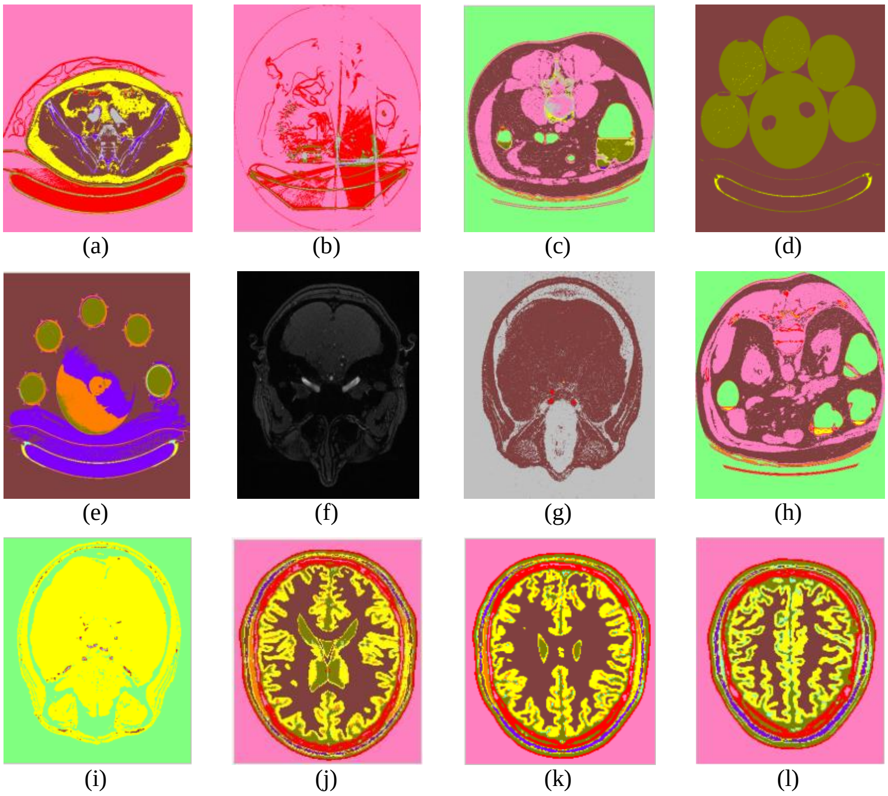


Figure 5. Segmented images

VI. Conclusion

In this paper, we have described a method that combines Hidden Markov Random Fields and Particle Swarm Optimisation to perform segmentation. Performance evaluation was carried out on sample medical images from the Brainweb database. From the tests we conducted, the HMRF-PSO combination method outperforms K-means and threshold based segmentation techniques. Otsu, MOG, and MOGG methods are very sensitive to noise. HMRF-PSO method demonstrates its robustness and resistance to noise.

Selecting parameters of the segmentation process by the HMRF-PSO method is not obvious. Tests conducted have focused on the images from the Brainweb database. Other image databases should be used to confirm the supremacy of the method. A comparison with other segmentation techniques must also be carried out.

The opinion of specialists must also be considered in the evaluation when no ground truth is available to have a more synthetic view of the whole segmentation process.

References

[1] E.D. Angelini, T. Song, B.D. Mensh, & A.F. Laine, "Brain MRI Segmentation with Multiphase Minimal Partitioning: A Comparative Study", Int. J. Biomed Imaging, volume 2007, 15p.

[2] Birge, B. (2003, April). PSOt-a particle swarm optimization toolbox for use with Matlab. In Swarm Intelligence Symposium, 2003. SIS'03. Proceedings of the 2003 IEEE (pp. 182-186). IEEE.

[3] A. Boulmerka, , & M.S. Allili, (2012, November). Thresholding-based segmentation revisited using mixtures of generalized Gaussian distributions. In Pattern Recognition (ICPR), 2012 21st International Conference on (pp. 2894-2897). IEEE.

[4] C.A., Cocosco, Kollokian, V., Kwan, R. K. S., Pike, G. B., & Evans, A. C. (1997). Brainweb: Online interface to a 3D MRI simulated brain database. In NeuroImage.

[5] A.P. Dempster, N.M. Laird, D.B. Rubin, "Maximum likelihood from incomplete data via the EM algorithm", Journal Royal Stat. Soc., B1:1-38, 1977.

[6] H. Deng, D.A. Clausi, "Unsupervised image segmentation using a simple MRF model with a new implementation scheme", Proceedings of the 17th International Conference on Pattern Recognition, Aug. 2004, 691- 694.

[7] R. Eberhart, & J., Kennedy, (1995, October). A new optimizer using particle swarm theory. In Micro Machine and Human Science, 1995. MHS'95., Proceedings of the Sixth International Symposium on (pp. 39-43). IEEE.

[8] R. Eberhart, & Y. Shi, (2000). Comparing inertia weights and constriction factors in particle swarm optimization. In Evolutionary Computation, 2000. Proceedings of the 2000 Congress on (Vol. 1, pp. 84-88). IEEE.

[9] A.P., Engelbrecht, (2005). Fundamentals of computational swarm intelligence (Vol. 1). Chichester: Wiley.

[10] S. Geman, D. Geman (1984). "Stochastic relaxation, Gibbs distributions and the Bayesian restoration of images". IEEE Trans. Pattern Anal. Machine Intell. 6 (6), 721-741.

[11] D.B. Gu, J.X. Sun, "EM image segmentation algorithm based on an inhomogeneous hidden MRF model", Vision, Image and Signal Processing, IEE Proceedings, Volume 152, Issue 2, 8 April 2005, 184 – 190.

[12] K. Held, E.R. Kops, B.J. Krause, W.M Wells, R. Kikinis, H.-W. Muller-Gartner, "Markov random field segmentation of brain MR images", IEEE Transactions on Medical Imaging, Dec. 1997, Volume: 16(6), 878-886.

[13] Z. Kato, J. Zerubia, M. Berthod, "Unsupervised parallel image classification using Markovian models", Pattern Recognition 32 (1999) 591-604.

[14] Kennedy, J. (2010). Particle swarm optimization. In Encyclopedia of Machine Learning (pp. 760-766). Springer US.

[15] S. Z. Li. Markov Random Field Modeling in Computer Vision. New York: Springer-Verlag, 2001.

[16] J.L. Marroquin, B.C. Vemuri, S. Botello, E. Calderon, Fernandez-Bouzas, A "An accurate and efficient Bayesian method for automatic segmentation of brain MRI", IEEE Transactions on Medical Imaging, vol.21(8), Aug. 2002, 934-945.

[17] Y., Shi, (2001). Particle swarm optimization: developments, applications and resources. In Evolutionary Computation, 2001. Proceedings of the 2001 Congress on (Vol. 1, pp. 81-86). IEEE.

[18] R. Szeliski, R. Zabih, D. Scharstein, O. Veksler, V. Kolmogorov, A. Agarwala, M. Tappen, and C. Rother, "A Comparative Study of Energy Minimization Methods for Markov Random Fields with Smoothness-Based Priors", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 30, No. 6, June 2008.

[19] I.C., Trelea, (2003). The particle swarm optimization algorithm: convergence analysis and parameter selection. Information processing letters, 85(6), 317-325.

[20] D.W. Van der Merwe,, & A.P. Engelbrecht, (2003, December). Data clustering using particle swarm optimization. In Evolutionary Computation, 2003. CEC'03. The 2003 Congress on (Vol. 1, pp. 215-220). IEEE.

[21] K. Van Leemput, F. Maes, D. Vandermeulen, and P. Suetens, "A Unifying Framework for Partial Volume Segmentation of Brain MR Images", IEEE Transactions on Medical Imaging, vol. 22, no. 1, pp.105-119, January 2003.

[22] P. Wyatt and J.A. Noble "MAP MRF joint segmentation and registration of medical images", Medical Image Analysis, Volume 7, Issue 4, December 2003, 539-552

[23] Y. Zhang, M. Brady, & S. Smith, "Segmentation of Brain MR Images Through a Hidden Markov Random Field Model and the Expectation-Maximization Algorithm", IEEE Transactions on Medical Imaging, Vol. 20, No. 1, January 2001, 45–57.