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Hidden Markov Random Fields and Swarm Particles: a Winning Combination in Image Segmentation

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Abstract

Segmenting an image, by splitting this latter into distinctive regions, is a crucial task in many nowadays ubiquitous applications. Several methods have been developed to perform segmentation. We present a method that combines Hidden Markov Random Fields (HMRF) and Particle Swarm Optimisation (PSO) to perform segmentation. HMRF is used for modelling the segmentation problem. This elegant model leads to an optimization problem. The latter is solved using PSO method whose parameters setting is a task in itself. We conduct a study for the choice of parameters that give a good segmentation. The quality of segmentation is evaluated on grounds truths images using Misclassification Error criterion. We use the NDT (Non Destructive Testing) image dataset to evaluate several segmentation methods. These results show a supremacy of the HMRF-PSO method over threshold based techniques.

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Keywords: Image segmentation, Hidden Markov Random Field, Swarm Particles Optimization, Misclassification Error.

1. Introduction

Image segmentation, a process used to partition images into distinctive and meaningful regions, is a crucial task in many nowadays ubiquitous applications. More specifically, in image segmentation, a label is assigned to each pixel in an image such that pixels having the same label have some common characteristics. Various

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techniques have been explored for image segmentation. We can classify these methods in six broad classes: 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. Geman and Geman [7] were among the precursors using Markov Random Fields (MRF) models in segmentation [3,8,9]. Our work focuses on image segmentation using HMRF model. This monetization results in an energy function minimization [2] under the MAP criterion (Maximum A Posteriori). For this purpose, we have used Particle Swarm Optimization (PSO) technique. PSO optimization is a class of metaheuristics formalized in 1995 by Eberhart and Kennedy [4]. This technique [6] is drawn from moving swarm social behaviour as flocking bird or schooling fish. An individual of the swarm is only aware of the position and speed of its nearest neighbours. Each particle modifies its behaviour on the basis of its experience and the experience of its neighbours to build a solution to a problem like a sardine shoal trying to escape tuna fishes. The performance of the swarm is greater than the sum of the performance of its parts. The selection of PSO parameters in the algorithm simulation is a problem in itself [5,11]. A bad choice of parameters can lead to a chaotic behaviour of the optimization algorithm. We conduct an evaluative study for the choice of parameters that give a good segmentation. The quality of segmentation is evaluated on ground truth images using the Misclassification Error criterion. We have used NDT (Non Destructive Testing) image dataset [10] to evaluate several segmentation methods. The results show the supremacy of the HMRF-PSO method over threshold based techniques.

This paper consists of six sections. 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 dedicated to conclusions.

2. Markov Random Field model

2.1 Neighbourhood system and cliques

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

$$\forall s \in S,\ s \notin Vs(S),\ \forall\{s,t\} \in S,\ s \in Vt(S) \Leftrightarrow t \in Vs(S) \qquad (2.1)$$

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

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

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:

$$\forall\{s,t\} \in c,\ t \in Vs(S) \qquad (2.3)$$

2.2 Markov Random Field

Let $X=\{X_1,X_2,\dots,X_M\}$ be a set of random variables on *S*. Every random variable takes its values in the space $\Lambda=\{1,2,\dots,K\}$. The set *X* is a random field with the configuration set $\Omega = \Lambda^M$. A random field *X* is said to be a Markov Random Field on S with regard to a neighbourhood system *V(S)* if the formula given hereafter holds:

$$\forall x \in \Omega,\ P(x) > 0,\ \forall s \in S,\ \forall x \in \Omega, P(Xs=xs/Xt=xt,t \neq s)=P(Xs=xs/Xt=xt,t \in Vs(S)) \qquad (2.4)$$

Equivalency betwixt Markov Random Fields and Gibbs fields is established by the theorem of Hammersley Clifford. The following equations characterize Gibbs distribution:

$$P(x)= Z^{-1}e^{-\frac{U(x)}{T}} \tag{2.5}$$

$$Z=\sum_{y\in\Omega} e^{-\frac{U(y)}{T}} \tag{2.6}$$

T is a control parameter well known as temperature; *Z* is a normalization constant referred to the partition function. *U(x),* potentials sum on all cliques *C* yields Gibbs field energy function:

$$U(x)=\sum_{c\in C} U_c(x) \tag{2.7}$$

3. Hidden Markov Random Field model

The input image is considered as realization of a Markov Random Field $Y=\{Y_s\}_{s\in S}$ defined on the lattice *S*. The random variables $\{Y_s\}_{s\in S}$ have values (representing grey levels) in the space $\Lambda_{obs}=\{0..255\}$. The configuration set is Ω_{obs}. The segmented image is considered as realization of a different Markov Random Field *X*, taking values in the space $\Lambda=\{1,2,\ldots,K\}$ *where K* is the number of classes or distinct parts of the image. An example, of observed image and hidden image, is shown in figure 1.

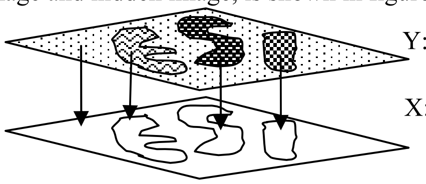

Fig. 1. Observed image and segmented image.

The segmentation process consists in finding a realization *x* of *X* by observing the data of the realization *y* of *Y,* where *y* representing the image to segment. So we seek a labeling $\hat{x}$ by maximizing the probability *P(X=x/Y=y)* or in an equivalent manner by the function $\Psi(x,y)$ minimization, knowing that δ is the Kronecker's delta and β is a constant greater than zero

$$\Psi(\mathrm{x},\mathrm{y})=\sum_{s\in S}\frac{(\mathrm{y_s}-\mu_{x_s})}{2\sigma_{x_s}^2}+\ln(\sqrt{2\pi}\sigma_{x_s})-\frac{\beta}{T}\sum_{\mathrm{s},t\in \mathrm{C}_2}(1-2\delta(x_s,x_t)) \tag{3.1}$$

4. PSO Particle Swarm Optimization

Particle Swarm Optimization is a powerful optimization method inspired by the social behaviour of animals living or moving in swarm like flocking bird or schooling fish. 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 modifies its behaviour on the basis of its experience and 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 a K-dimensioned space of possible solutions which change at time *t+1* by a velocity $v_i(t)$. The velocity $v_i(t)$ is influenced by $y_i(t)$ the best position visited by itself (its experience) and $\mathrm{z_i(t)}$ the best position of all particles (we call it, the global best). The positions are measured by a fitness function f.

$x_i(t) = (x_{i1}, x_{i2}, \dots, x_{ij}, \dots, x_{iK})$ *:* position of particle *i* at time *t*.
$v_i(t) = (v_{i1}, v_{i2}, \dots, v_{ij}, \dots, v_{iK})$: velocity of particle *i* at time *t*.
$y_i(t) = (y_{i1}, y_{i2}, \dots, y_{ij}, \dots, y_{iK})$: best position of particle *i* till time t.
$z(t) = (z_1, z_2, \dots, z_j, \dots, z_K)$: best position of all particles till time t.
y_i is updated over time according to the following formula:

$$y_i(t+1) = \begin{cases} y_i(t) & if\ f(x_i(t+1)) \geq f(y_i(t)) \\ x_i(t+1) & if\ f(x_i(t+1)) < f(y_i(t)) \end{cases} \qquad (4.1)$$

The best position $\mathrm{z(t)}$, reached by all the particles till time *t,* will be calculated for a swarm size *s* by the formula:

$$z(t) \in \left(y_1(t), y_2(t), \dots, y_k(t), \dots, y_s(t)\right) = min\{f(y_1(t)), f(y_2(t)), \dots, f(y_k(t)), \dots, f(y_s(t))\} \qquad (4.2)$$

The velocity $v_i(t) = (v_{i1}(t), v_{i2}(t), \dots, v_{ij}(t), \dots, v_{iK}(t))$ of the particle *i* at the time *t* is updated by:

$$v_{ij}(t+1) = w * v_{ij}(t) + c1 * r_{1j} * \left(y_{ij}(t) - x_{ij}(t)\right) + c2 * r_{2j} * \left(z_j(t) - x_{ij}(t)\right) \qquad (4.3)$$

Where *w* is called the inertia weight, *c1* and *c2* are the acceleration constants. r_{1j} and r_{2j} are random variables in interval [0-1]. Velocity v_{ij} is limited by V*max* to ensure convergence. The position x_i of the particle *i* is updated by:

$$x_i(t+1) = x_i(t) + v_i(t+1) \qquad (4.4)$$

The PSO algorithm is summarized hereafter:

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

5. Experimental Results

In HMRF-PSO combination, we have used PSO method to minimize the formula (3.1) given by the MAP estimator. Each particle displacement is defined as: $x_i(t) = (\mu_{i1}, \mu_{i2}, \ldots, \mu_{ij}, \ldots, \mu_{iK})$; K is the number of distinctive parts in the image, μ_{ij} is j^{th} mean of the i^{th} particle and $f=\Psi$ is the fitness function. After several tests conducted, PSO parameters have been set to: size=80, c1=0.7, c2=0.8, w=0.7, vmax=5, iteration_number=100 and B=1. Six NDT images, their ground truth and the segmented images using HMRF-PSO are shown in figure 2.I, figure 2.II and figure 2.III respectively.

(a) (b) (c) (d) (e) (f)

I

II

III

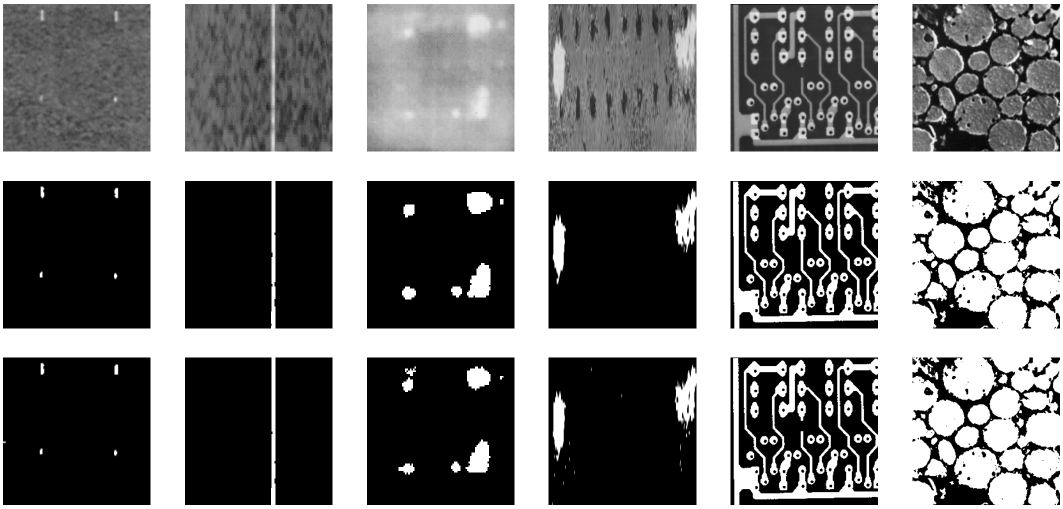

Fig. 2. (I) original images; (II) ground truth images; (III) result of segmentation using HMRF-PSO method

We performed several tests to assess performance of the method used in our work by comparing it to ten threshold-based methods [1] that are: Otsu method, Median extension, Mixture Of Gaussians (MOG), Mixture Of Generalized Gaussians (MOGG), Abutaleb, Kittler-Ill, Kapur et al, Li & Lee, Pham, SemiV and Tsai. For this purpose, we have used NDT images. Misclassification Error ME criterion is used as the performance metric in the comparison. For binary image (constituted by a foreground and a background) segmentation, ME gives the percentage of misclassified pixels, defined as follows:

$$ME = 1 - \frac{|B_O \cap B_T| + |F_O \cap F_T|}{|B_O| + |F_O|} \qquad (5.1)$$

Where F_O and B_O indicate foreground and background of ground truth (or original) image, F_T and B_T indicate foreground and background in the segmented image. For a perfect match of segmented classes with ground-truth regions, ME is zero. ME equals one if there all pixels are misclassified.

In table 1, are given the misclassification errors in the segmented images obtained by the eleven methods used on the six NDT images shown in figure 2.I. The results clearly show the superiority of the HMRF-PSO method.

6. Conclusion

We have described a method that combines Hidden Markov Random Fields and Particle Swarm Optimisation to perform segmentation. A statistical study was carried out to set the parameters of the method. Performance evaluation was conducted on NDT image dataset. Misclassification Error criterion was used as a performance metric. From the results obtained, the HMRF-PSO combination method outperforms threshold based segmentation techniques. These latter are very sensitive to noise. HMRF-PSO method demonstrates its robustness and resistance to noise.

Table 1 Misclassification errors in NDT segmented images

Method	Image (a)	Image (b)	Image (c)	Image (d)	Image (e)	Image (f)
Abutaleb	0.023	0.310	0.023	0.024	0.250	0.620
Kittler-Ill.	0.000	0.003	0.037	0.008	0.025	0.028
Kapur et al.	0.003	0.004	0.028	0.036	0.220	0.620
Tsai	0.240	0.170	0.350	0.290	0.084	0.280
Li & Lee	0.490	0.550	0.450	0.710	0.021	0.020
Pham	0.460	0.560	0.021	0.760	0.048	0.250
SemiV	0.003	0.004	0.026	0.018	0.062	0.160
Otsu	0.462	0.513	0.413	0.021	0.037	0.074
Median extension	0.462	0.527	0.474	0.608	0.028	0.039
MoG	0.000	0.000	0.032	0.010	0.018	0.012
MoGG	0.000	0.000	0.028	0.007	0.012	0.016
HMRF-PSO	0.000	0.000	0.018	0.001	0.004	0.005

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