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A New Bias Field Estimation Method based on Adapted PSO Method

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Abstract

It is hard to segmentation brain MR images for the bias fields. In this paper, a new fuzzy anisotropic diffusion function is presented to reduce the effect of the noise. We use Legendre polynomial functions to reconstruct the bias field, which make the entropy of the recovered image be smallest. But it needs to compute a lot of parameters to reconstruct the bias. The traditional method uses the gradient descending method to compute the parameters. The method plunges into local best easily. In order to deal with this problem, Particle swarm optimization (PSO) method is analyzed. A new particle swarm technique is proposed that incorporates initial location information and use mutate operation make the particles away from local maxima. The experiments show that the new method can get accurate result robustly.

Keywords: *fuzzy anisotropic diffusion, entropy, genetics algorithm, Particle swarm optimization, local maxima, global maxima*

1. Introduction

Intensity inhomogeneity, which is also named bias field, usually makes the intensity of the same tissue varies with the location of the tissue. Therefore, correction for such intensity inhomogeneities is often a mandatory step before quantitative analysis of the image data.

Accurate segmentation of magnetic resonance (MR) images of the brain is of interest in the study of many brain disorders. The segmentation experiments presented by Jungke et al [1] illustrate that the major problem was not noise but rather inhomogeneity. A widely used model for intensity inhomogeneity is to lump all sources of inhomogeneity in one multiplicative factor: the bias fields. The observed MRI signal Y is the produce of the true signal X generated by the underlying anatomy and spatially varying field factor B, and an additive noise N. At the pixel i:

$$y_i = x_i b_i + n_i \tag{1}$$

Given the observed signal Y, the problem is to estimate the true image X. The solution is not trivial since the bias field is also unknown.

Some correction techniques rely on measuring the coil sensitivity function using a physical phantom [2, 3]. These approaches can correct for coil sensitivity but do not correct for other sources of intensity inhomogeneity. Many image processing methods have been proposed to estimate the bias field directly from the image Y. To separate the underlying "true" image X, from the bias field B, assumptions can be made on X and/or on B.

A key observation is that the bias field is smooth compared to a typical MR image and most, if not all, methods rely on this fact. The smoothness of B can be constrained in the

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frequency domain assuming that its spectrum contains low frequencies that do not significantly overlap with the relatively “high frequency” image spectrum [4]. These methods are very attractive since no other assumption X or B is necessary and well-known low-pass filtering schemes can be implemented. But these methods may lose the edge information and make the results inaccurate.

Attempts have been made to separate and in the image domain by constraining to be smooth using a model. Proposed models, in order of increasing expressiveness, are: polyno- mial functions [5], thin plates like constrained membrane [6]. Classifications schemes [7] can then be used to estimate B .Due to the very high intensity in homogeneity present with phased array coils, clusters are spread over large regions in feature space, thus increasing the sensitivity to initial conditions and local minima. Some researchers do not segment the image into classes, instead, they maximize the information content in X .

In this paper we introduce fuzzy anisotropic diffusion function to reduce the effect of the noise. The fuzzy anisotropic diffusion function can reduce the effect of the noise and preserve the edge information. After skull stripping the non brain tissues, we use the Legendre polynomials as the base functions to construct the bias field B' and get the restoration image X'. Every X' has its entropy and the minima one is the best one. To research the best bias it need to find many parameters of the Legendre polynomials. Gradient descending method is one of the traditional methods but it is easily to trapped to local maxima. In this paper we use an adapted Particle swarm optimization (PSO) to compute the parameters. *This paper is a revised and expanded version of a paper [12] presented at international conferences on ISA, CIA 2015 in Philippines.*

2. Methods

2.1. Skull Stripping

In the brain images the background and non brain tissues take a large part, and in the background there is no bias information, an accurate skull stripping method will help analyzing the bias field. In this paper, we used an improved skull stripped method to obtain brain tissues [8]

2.2. Fuzzy Anisotropic Diffusion Function

n order to reduce the effect of noise, we apply an anisotropic diffusion filter that smoothes noisy regions in the image while preserve edge boundaries.

Anisotropic diffusion filtering was proposed as an image processing method by Perona and Malik [9]. The filtered image is modeled as the solution to the anisotropic diffusion equation:

$$\partial_t u = div(g(|\nabla u|)\nabla u) \qquad (1)$$

Where u is the image, $u(0) = u_0$ is the initial image, ∇u is the gradient of the image, $g(X)$ is the diffusion function to control the diffusion strength:

$$g(X) = \begin{cases} 1 & X \le 0 \\ 1 - \exp(\dfrac{-3.315}{(X/\lambda)^4}) & X > 0 \end{cases} \qquad (2)$$

Where λ is the diffusion constant. If $|\nabla u| > \lambda$ then the point will be regard as the edge point and the $g(X)$ is small; when $|\nabla u| \le \lambda$ the point will be in object or in background and the $g(X)$ is near to 1. $g(X)$ depend on the choice of the λ , when the point is a strong noise, the $g(X)$ on the point is small too. So it is hard to smooth strong noise. To deal with this problem we adapt the diffusion function:

$$g(X)=\begin{cases}1 & X\le 0\\ 1-\exp(\frac{-3.315}{(X/\lambda)^4}) & f(x)\le T\\ f(x) & f(x)>T\end{cases} \quad (3)$$

Where T is constant, $f(x)$ is the region information of the point x :

$$f(x)=1-\exp(-(|u(x)-u_{mean}(x)| + |\nabla u(x)-\nabla u_{mean}(x)|)) \quad (4)$$

$u(x)$ is the intensity of point x , $u_{mean}(x)$ is the mean intensity of the region around x , $\nabla u(x)$ is the gradient of x , $\nabla u_{mean}(x)$ is the mean gradient around x . When x is a strong noise point, the $f(x)$ is bigger then others and the set the diffusion function $g(X)$ to be $f(x)$ to smooth x , and when x is not a strong noise point, $g(X)$ does not change; when the point is on the edge $f(x)$ is smaller than the one of strong points. Using this equation the strong noise can be smoothed and edge information be preserved.

2.3. Bias Field Model

A two-dimensional (2-D) polynomial function of order l is used to provide an initial estimate of the bias field:

$$b(x,y)=\sum_{i=0}^{l}\sum_{j=0}^{l-i} p_{ij}P_i(x)P_j(y) \quad (5)$$

The polynomial function is fitted in a least square sense to the tissue pixels using a classic regression technique. To improve upon the description of the bias field, we use Legendre polynomial functions, for they are orthogonal polynomial functions. Where p_{ij} is the parameter, the location of the pixels should be convert to [-1, 1], in order to get better result we set $l=4$, at this time, the model must compute $(l+1)(l+2)/2=15$ parameters.

2.4. Entropy Optimization

It has been proved that the best bias field can make the entropy of the corrected image be minimum. The Legendre polynomial functions estimate of the bias field is optimized so as to minimize the entropy of the image. Entropy is given below where $pdf(l)$ is the probability density function of image X , which is approximated by the histogram of the voxels in the area being optimized, divided by the number of voxels:

$$I(X)=-\sum_{l\in\{gray\ level\}} pdf(l)\log(pdf(l)) \quad (6)$$

2.5. Algorithm Parameters

Different parameter can get different bias field. Gradient descent method is one of the wide used methods, but when the order of the polynomial is high it need to compute a lot of parameter and easy to trapped into local maxima. In order get the global best result we PSO method to compute the parameters.

Algorithm Parameters based on GA

The GA [10] is a stochastic global search method that mimics the metaphor of natural biological evolution. In this paper we use GA compute the parameter.

Step1 construct the initial population

As an example we set $l = 4$, and have 15 parameters to compute. Each individual is a 1*15 matrix. Randomly choose 15 numerical values in [-10 10] as the individual. We analyze more than 1000 brain MR images and find that the numerical value of the bias field is more than 0.25. If the bias, got by the parameter, is less than 0.25, the individual should be reinitialized.

Step2 compute the fitness function:

$$f = 1/I(X_{\Omega}) \tag{7}$$

Where $I(\cdot)$ is function (6) and X_{Ω} is image of the brain tissues region.

Step3 Selection operator

Compute the probability of every individual in the population:

$$P(i) = \frac{f(i)}{\sum_{i=1}^{N} f(i)} \tag{8}$$

Construct a roulette to select which individual be selected to next iteration.

Step4 Crossover Operator

Crossover the individuals depend on the cross probability p_{c}. Suppose that $X_i^{(t)}$、$X_j^{(t)}$ will crossover then the two new individual is:

$$\begin{cases} \mathbf{X}_i^{(t+1)} = w\mathbf{X}_j^{(t)} + (1-w)\mathbf{X}_i^{(t)} \\ \mathbf{X}_j^{(t+1)} = w\mathbf{X}_i^{(t)} + (1-w)\mathbf{X}_j^{(t)} \end{cases} \tag{9}$$

Where w is constant. Judge the bias fields, computed by the parameters, whether less than 0.25, if less than 0.25 repeat the operation.

Step5 Mutation Operator

Mutate the individual depend on the Mutation probability p_{m}. If $X_i^{(t)}$ is selected, then change one of its parameter in [-10 10], and judge the bias field.

Step6 repeat step 2 to step 5 until achieve the stop requirement.

In this paper we set N =50~100, p_{c} =0.4~0.9, p_{m} =0.0001~0.01, the max iterative num $\hat{T}$ =500~2000。

Algorithm Parameters based on PSO

PSO [11] is one of the evolutionary optimization techniques proposed by Kennedy and Eberhart. The basic idea of PSO was inspired by natural flocking and swarm behavior of birds and insects. Analogous to GA, PSO is also a population-based iterative algorithm, and starts with a population of randomly generated solutions called particles, which evolve over generations in approaching the optimum solution by the following rules:

Each particle is treated as a point in a D-dimension space, and the ith particle is represented as $X_i = (X_{i,1}, X_{i,2}, ..., X_{i,D})$. Each particle has a fitness measure f_i, which is the performance measure of the function or system being optimized, and the velocity $\boldsymbol{V}_i$ and position in the hyperspace of a particle are tracked. Each particle's best position that corresponds with the minimum fitness measure achieved so far in the search process is denoted as $pbest_i$. Likewise, the best position of all particles in the population achieved so far is denoted as $gbest$. Both $pbest_i$ and $gbest$ are constantly updated over iterations in seeking the optimum.

Once the $pbest_i$ and $gbest$ are identified in current iteration, each particle updates its velocity and position by Equations (10) and (11) prior to starting the next iteration.

$$\mathbf{V}_i(t+1) = \mathbf{V}_i(t) + \varphi_1 u_1(pbest_i - X_i(t)) + \varphi_2 u_2(gbest - X_i(t)) \quad (10)$$

$$X_i(t+1) = X_i(t) + \mathbf{V}_i(t+1) \quad (11)$$

Where φ_1 and φ_2 are the cognitive parameter and the social parameter respectively, both of which are generally set as 2.05; u_1 and u_2 are random numbers uniformly distributed on the range (0, 1). PSO method used to compute parameters include these steps:

GA and PSO are easily trapped into local optima, in order to deal with this problem, we introduce the initial information to the model:

$$\mathbf{V}_i(t+1) = \chi[\mathbf{V}_i(t) + \varphi_1 u_1(pbest_i - X_i(t)) + \varphi_2 u_2(gbest - X_i(t)) + \varphi_3 u_3(X_i(0) - X_i(t))] \quad (12)$$

$$\varphi_3 = \exp(-\|pbest - gbest\|) \quad (13)$$

$$\varphi = \varphi_1 + \varphi_2 + \varphi_3, \quad \varphi > 4 \quad (14)$$

When particle X_i is near to $gbest$, X_i will be pull back by the initial position information, with this information the particle can search more areas so the model can break out from local position easier.

In order to let the method break out from local best, we add a mutation operation. After step4 we choose 5% particles, whose fitness is worst, and mutate them with these rules:

Suppose X_i is a particle to be mutated, if $\exp(-\|pbest - gbest\|) \geq T$, T is a constant, it is obvious that X_i is near to $gbest$. At this condition we define an area R', whose centre is $gbest$ and radius is r_i. Randomly set X_i be a new point $X_i^{'}$ in the area $R - R'$, where R is the research region. The bias computed by $X_i^{'}$ must bigger than 0.25.

$$r_i = r_{\max} \exp(-\|pbest - gbest\|) \quad (15)$$

Where $r_{\max}$ is half of the research region's radius. If $\exp(-\|pbest - gbest\|) < T$, X_i is far to $gbest$, and if $gbest$ is near to global best, X_i need to move to $gbest$, else if X_i is near to global best, X_i need to research around itself. But we don't know where is global best, so at this condition we use Powell method to adapt X_i.

Our adapted PSO method includes these steps:

Step1 construct the initial particles.
Step2 Use Eq (7) to compute all the particles' fitness.
Step3 Update $pbest_i$ and $gbest$
Step4 Use Eq (13) and (12) to update each particle
Step5 mutate the worst 5% particles
Step6 repeat Step2 to Step5 until achieve the stop requirement

3. Implementation and Results

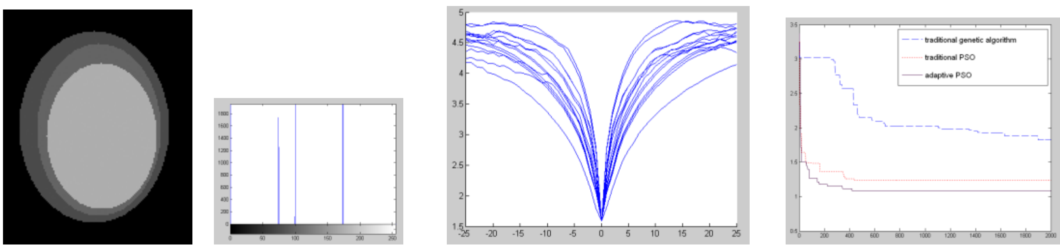
We have implemented the genetic algorithms, particle swarm optimization method and adapted PSO method using Matlab language. We have run programs on a PC platform.

A 136*168 image was generated with three tissue classes have gray values of 75, 100 and 175. The histogram of the image is shown in Fig 1.b. Fig 1.c shows the entropy of image Figure 1.a, when obly one parameter varies. Although the minimum values are well defined, the functions are not smooth. The histogram of the image X_{bias} is shown in Figure 1.e.2, the bias fields is show in Figure 1.e.3. From the histogram we can not find obvious distinguish between classes. Use Gauss Mixture Model classify the image X_{bias} and get the results showed in Figure 1.f.1to Figure 1.f.3. With the effect of the bias field the method get wrong results. Figure 1.g.3 is the bias field B_g computed by the gradient descent method, and the recovered image X_g is show in Figure 1.g.1. F1.g.2is the histogram of the recovered image and B_g is not well enough and the recovered image X_g still has bias field. The results of GMM on Figure 1.g.1 are shown in Figure 1.g.4 to Figure 1.g.6. The results are not well enough too. Figure 1.h.3 is the bias field B_G got by GA method and Figure 1.h.1 is the recovered image X_G , Figure 1.h.2 is the corresponding histogram. From the histogram, we can see that there are three classes in the histogram, it is better than that of gradient descent method, but GM and CSF are not separated, so there are some mistakes in the results segmented by GMM. Figure 1.i.1 to Figure 1.i.6 is recovered image X_P , corresponding histogram, bias field B_P , segmentation of WM, GM, CSF, respectively, by using PSO method. Figure 1.j.3 is the bias field B_{AP} get by the adapted PSO method, Figure 1.j.1 is the recovered image X_{AP} Figure 1.j.2 is the histogram. From this histogram we can find that the three classes have been separated. And the result, shown in Figure 1.j.4 to Figure 1.j.6, is better than those of GA method and PSO method. Figure 1.d is the optimization procedure by GA method, PSO method and adapted PSO method. It is clear for the figure that solution obtained by adapted PSO converges to high quality solutions. The average iteration to the best result by adapted PSO method is less than 500.

Figure 2.a is a true brain MR image with the size 190*254, the image has strong bias field and noise, Figure 2.b is skull stripped image. Figure 2.c is the histogram. The second line to the end line show the results of gradient descent method, GA, PSO, APSO, respectively. Use Eq (17) to compute the veracity of the four methods.

$$J(S_1,S_2)=\frac{|S_1 \cap S_2|}{|S_1 \cup S_2|} \tag{17}$$

S_1, S_2 are the exact result and the result got by method, which need to be analyze, respectively. The veracity of the four methods is shown in table 1.



a. initial image b. histogram c. entropy distribution d. iteration

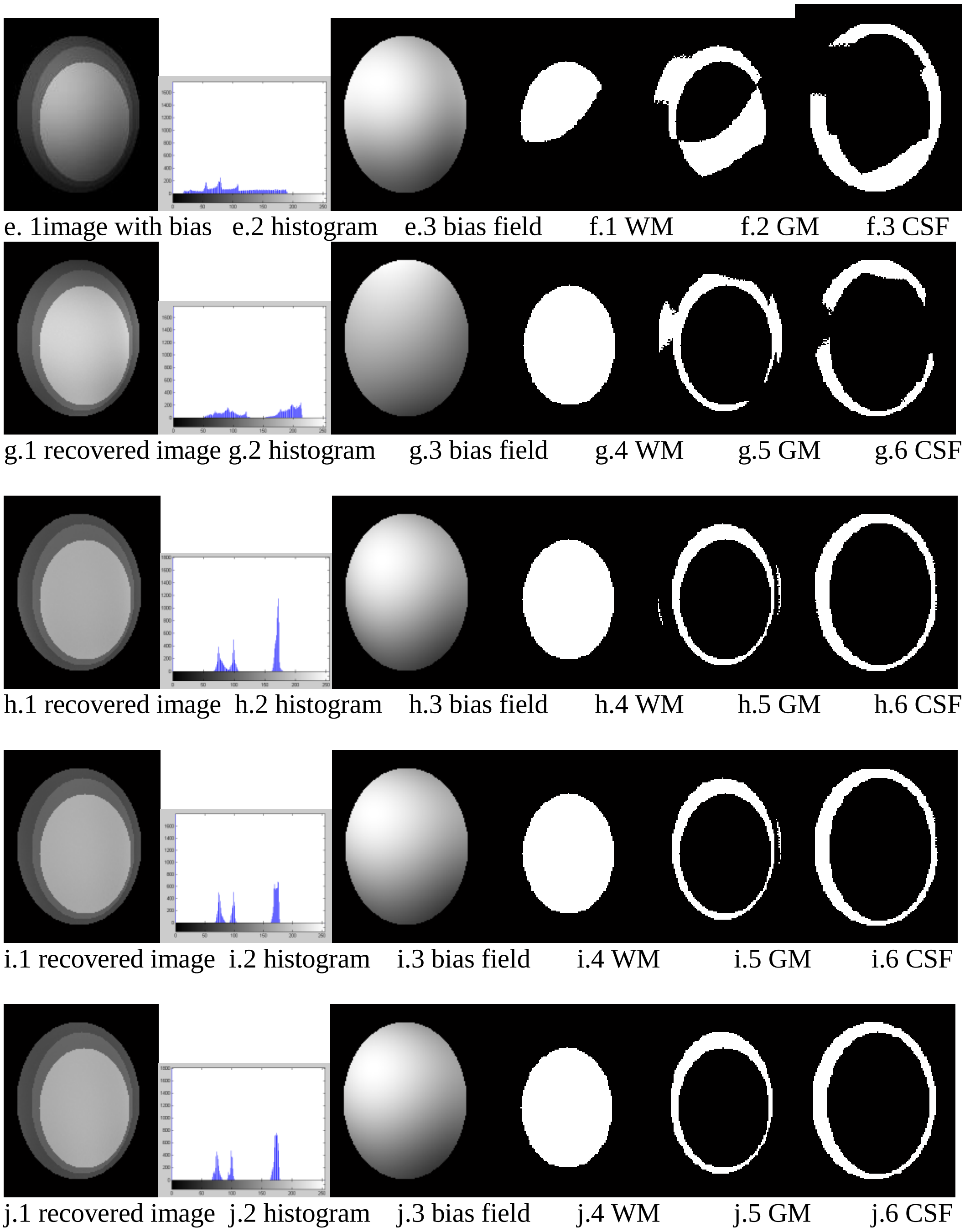
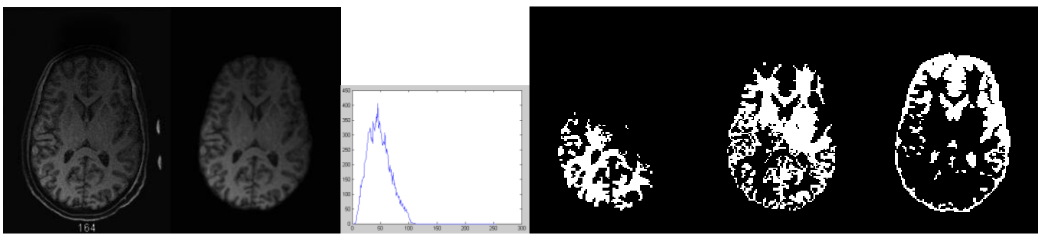


Figure 1. Artificial Image Segmentation



a. initial image b. image be skull stripped c histogram d.1 WM d.2 GM d.3 CSF

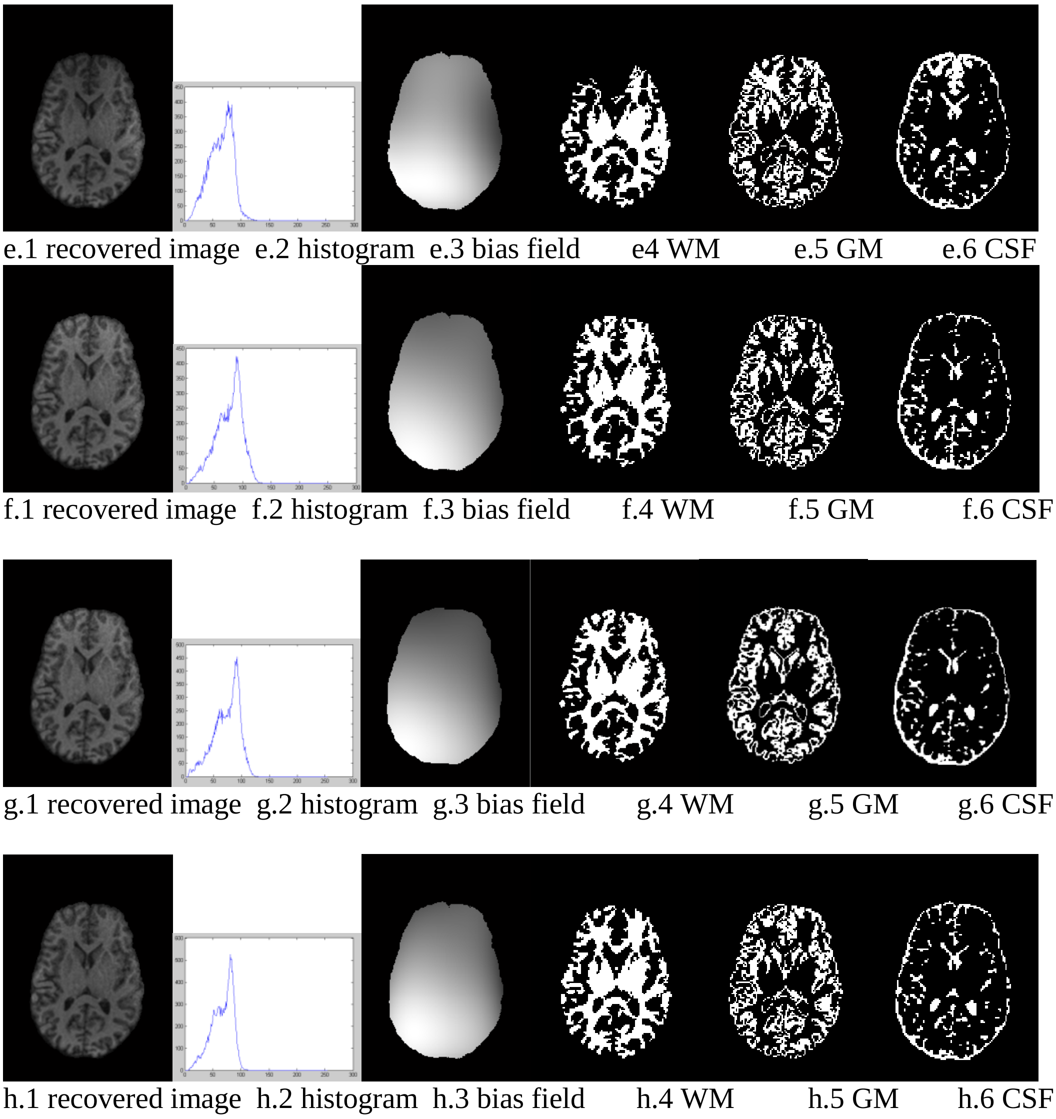


Figure 2. Brain MR Image Segmentation

Table 1. Veracity of Segmentation

	WM	GM	CSF
gradient descent method	77.69%	62.09%	70.25%
GA method	89.26%	80.55%	83.97%
PSO method	91.28%	83.29%	85.49%
adapted PSO method	99.25%	98.76%	97.88%

4. Conclusion

A new fuzzy anisotropic diffusion is present to reduce the effect of the noise. A new adaptation of particle swarm optimization specifically designed for brain MR image de bias was proposed in this paper. Experimental results for adapted PSO method compare with GA method PSO method and gradient descent method show that the adapted PSO method is more accuracy and efficiency.

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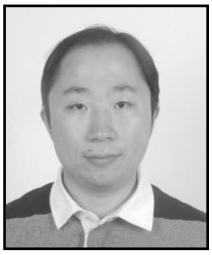

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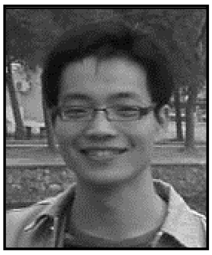

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