Image segmentation method based on fuzzy Markov random field

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Received 1 October 2014, www. Cmnt.lv

Abstract

Fuzzy theory is introduced into the Markov random field model, a kind of algorithm for image segmentation based on fuzzy MRF model is put forward. Firstly the definition of membership function is given. Then fuzzy prior distribution and likelihood distribution are given. The specific steps of segmentation algorithm based on fuzzy MRF model are carried out. The simulation results show that the proposed segmentation algorithm based on the fuzzy MRF model can better deal with the problems of overlapped gray, partial volume effect, and low contrast. It also has more accurate segmentation effect.

Keywords: image segmentation, fuzzy theory, Markov random field

1 Introduction

With the development of science and technology, image technology has received enough attention and rapid development. Among them, the image segmentation is one of the key technologies of digital image processing, and is also a hotspot in current image research. Image segmentation is the key step of image analysis, and segmentation quality directly affects the progress of the follow-up work.

Markov Random Field was used for image segmentation, which was mainly based on the pioneering work of Geman D and Geman S in 1984 [1]. Gibbs distribution and simulated annealing algorithm was introduced into the image restoration, and MRF method to solve the problem of image processing is put forward, namely the Maximum A Posteriori probability method (MAP). Since then, MRF model has been successfully applied in the field of image segmentation. Geman S, et al. also discussed neighborhood system, energy function, Gibbs sampling method of MRF model in detail, put forward SA algorithm for minimizing the energy function, and put forward convergence testification of SA algorithm to provide a theoretical basis for image processing based on MRF model. Mage segmentation by data-driven Markov Chain Monte Carlo was proposed by Zhuowen Tu [2]. Segmentation of brain MR images through a hidden Markov random field model and the expectation maximization algorithm was proposed by Zhang Y [3]. A novel MRF-Based image segmentation algorithm was proposed by Yimin Hou [4]. Constrained Markov random field model for colour and texture image segmentation was proposed by Dey R [5]. A new MRF framework with dual adaptive contexts for image segmentation was proposed by Ping Zhong [6]. Distributed local MRF models for tissue and structure brain segmentation were proposed by Benoit Scherrer [7]. Prostate cancer segmentation with simultaneous estimation of Markov Random Field parameters and class was proposed by Xin Liu [8]. Markov Random Field energy minimization method via iterated cross entropy with partition strategy was proposed by Jue Wu [9]. An unsupervised segmentation method using Markov Random Field on region adjacency graph for SAR images was proposed by Gui-song Xia [10]. Bayesian region growing and MRF-based minimization for texture and colour segmentation was proposed by Grinias I [11]. A comparative study of energy minimization methods for Markov Random Fields with smoothness-Based priors was proposed by Richard Szeliski [12]. A novel pixon representation for image segmentation based on Markov random field was proposed by Lei Lin [13]. SAR image segmentation based on mixture context and wavelet hidden-class-label Markov random field was proposed by Ming Li [14]. Fuzzy theory is introduced into Markov random field to solve fuzziness and randomness of image segmentation here. EM image segmentation algorithm based on an inhomogeneous hidden MRF model was proposed by Gu D-B [15]. Segmentation of the left ventricle from cardiac MR images using a subject-specific dynamical model was proposed by Yun Zhu [16]. Mixture models with adaptive spatial regularization for segmentation with an application to FMRI data was given by Woolrich [17]. Efficient segmentation method by sparse pixel classification was proposed by Erik B [18]. Mixed-State Markov random fields for motion texture modelling and segmentation was written by Crivelli T [19]. LCG-MRF-Based segmentation of MRI brain images was proposed by Hongmei Sun [20]. Prostate cancer

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segmentation with simultaneous estimation of Markov random field parameters and class was given by Xin Li [21].

The paper is organized as follows. In the next section, image segmentation model based on Markov random field and fuzzy theory is investigated. In Section 3, the process of Markov random field combing with fuzzy theory is given. In Section 4, in order to test segmentation accuracy of proposed algorithm, two images are used for the experiment. Finally, some remarks are given.

2 Image segmentation model based on Markov random field and fuzzy theory

In the traditional segmentation, segmentation result is non-overlapped in the label field, and there is only one type of pixel label, which is also known as a certain class of hard segmentation. If each pixel can gains different label value in different degree simultaneously, and the overlapped value turns up in a membership form, then it is called fuzzy segmentation (soft segmentation). In the proposed model, fuzzy label field of each pixel belonging to a certain class is obtained. After filed defuzzification, deterministic label field is obtained. In the proposed model, the three fields are used.

Y represents observation field, $Y=\{y[i,j]\,|\,1\le i\le H,\,1\le j\le W\}$, $y[i,j]$ represents gray value of pixel point $[i,j]$. X represents fuzzy random label field, $X=\{x[i,j]\,|\,1\le i\le H,\,1\le j\le W\}$. Supposing the image can be separated into L number of different classes, and then the value of each pixel point is from $\Omega=\{1,2,...,L\}$. Ω Is label space set. Pixel point is endowed with fuzzy set $u_{ij\lambda}$, $u_{ij\lambda}$ represents the probability that pixel $[i,j]$ belongs to the λ-th category, $\sum u_{ij\lambda}=1$. When X is constrained by Markov property, it is called fuzzy Markov random field. When X loses fuzzy property, it is called classic Markov label field Z. The deterministic label field Z, $Z=\{z[i,j]\,|\,1\le i\le H,1\le j\le W\}$, $z[i,j]\in\Omega$. Z has the same parameters with fuzzy random field X, which plays the role of connecting X and Y. The image segmentation problem can be expressed as optimized problem shown in Equation (1).

$$X^*=\arg\max_x\{\ln(P(Y\,|\,X)P(X))\}. \tag{1}$$

After Prior distribution $P(X)$ and likelihood distribution $\ln(P(Y|X)$ are gotten, the fuzzy Markov random field is obtained.

Setting up membership based on spatial information can reduce overlapped pixels to find out clear boundary. N_λ represents the number of adjacent pixels which belongs to the λ-th category and the membership function is defined in Equation (2).

$$\tilde{U}:L\to[0,1],$$

$$\lambda\to\tilde{U}(\lambda)=\frac{N_\lambda}{\sum_\lambda N_\lambda} \tag{2}$$

$\tilde{U}(\lambda)$ represents membership that pixel $[i,j]$ belongs to λ-th category. When the output fuzzy quantity is get, defuzzification method must be used to transform fuzzy quantity to an explicit quantity. The maximum membership method is adopted as shown in Equation (3).

$$x^*=\arg\min U(x) \tag{3}$$

3 The process of Markov random field combing with fuzzy theory

X Obeys Gibbs distribution as shown in Equation (4).

$$P(X)=\frac{1}{Z}e^{-\frac{U_2(X)}{T}}, \tag{4}$$

Z represents normalized constant, $U_2(X)$ represents fuzzy prior energy function, and T is a constant.

$$U_2(X)=\sum_{[\mathrm{i,j}]}\frac{\beta}{2}\left(\left\|x_{ij}-x_{mn}\right\|\right)\cdot\frac{(Y_c+\sigma_\lambda^2)}{\sigma_\lambda^2}, \tag{5}$$

$$Y_c=a\cdot\sqrt{\sum_{[\mathrm{m,n}]\in \mathrm{m}_{ij}}(y[\mathrm{i,j}]-\mathrm{y}[\mathrm{m,n}])^2},$$

$$\lambda\in\{1,2,...,L\},\quad a\in[0.5,3],\quad \beta\in[0.9,1.2].$$

$$\left\|x_{ij}-x_{mn}\right\|=\sum_{[m,n]\in m_{ij}}\sum_{\lambda=1}^{L}|u_{ij\lambda}-u_{mn\lambda}|, \tag{6}$$

$$P(Y/X)=\prod_{[\mathrm{i,j}]}\left\{\frac{1}{2\pi\sigma}\exp\left(-\frac{(y[i,j])-\mu)^2}{2\sigma^2}\right)\right\}, \tag{7}$$

$$\mu=\sum_{\lambda=1}^{L}\mu_{ij\lambda}\mu_\lambda,\quad \sigma^2=\sum_{\lambda=1}^{L}\mu_{ij\lambda}\sigma_\lambda^2,$$

then the optimized model is

$$X^*=\arg\min_x\left\{\sum_{[i,j]}\left[\frac{(y[i,j]-\mu)^2}{\sigma^2}+\ln(\sigma^2)\right]+U_2(X)\right\}, \tag{8}$$

$$U_1(Y\,|\,X)=\sum_{[i,j]}\left[\frac{(y[i,j]-\mu)^2}{\sigma^2}+\ln(\sigma^2)\right],$$

the model can be expressed as

$$X^*=\arg\min_x\{U_1(Y/X)+U_2(X)\}, \tag{9}$$

$U_1(Y|X)$ represents fuzzy likelihood energy and $U_2(X)$ represents fuzzy prior energy. The process of fuzzy Markov random field is as follows.

Step 1. The image is divided into L categories, and the initial classic label field Z^0 is obtained by means of traditional method.

Step 2. Initial mean value $\mu_\lambda^{(0)}$ and initial variance $\sigma_\lambda^{2(0)}$ of each category are obtained according to $Z^{(0)}$.

Step 3. Carry out defuzzification for $Z^{(0)}$ and initial label field $X^{(0)}$ is obtained according to Equation (2).

Step 4. SAR algorithm [14] is used to update X.

$$X^{k+1} = \arg\min_x \left\{ \sum_{[i,j]} \left[\frac{(y[i,j]-\mu^{(k)})^2}{\sigma^{2(k)}} + \ln(\sigma^{2(k)}) \right] + U_2(x^{(k)}[i,j]) \right\}$$

Step 5. Carry out defuzzification for X according to the principle of maximum membership and classic random field $Z^{(k+1)}$ is obtained.

Step 6. Update $\mu_\lambda^{(k+1)}$ and $\sigma_\lambda^{2(k+1)}$ according to Equation (10).

$$\mu_\lambda^{(\mathrm{k+1})} = \frac{\sum_{x[\mathrm{i,j}]} y[i,j]}{N},$$

$$\sigma_\lambda^{2(\mathrm{k+1})} = \frac{\sum_{x[\mathrm{i.j}]} (y[i,j]-\mu_\lambda)^2}{N}. \quad (10)$$

Step 7. Repeat step 4 to step 6, until the algorithm converges. Then output the result.

4 Numerical examples

In order to test the performance of proposed fuzzy Markov random field algorithm, Lena gray image shown in Figure 1 and brain MR image shown in Figure 2 are used for experiment. The simulation software is MatlabR2007b. The computer is Intel(R) Pentium(R) Dual CPU 2.00GHz with 956MB DDR2 SDRAM. The system software is Windows 7.

The segmentation effect of Lena image based on MRF is shown in Figure 3 and segmentation effect of Lena image based on proposed fuzzy MRF is shown in Figure 4. The segmentation effect of brain MR image based on MRF is shown in Figure 5 and segmentation effect of brain MR image based on proposed fuzzy MRF is shown in Figure 6. Because of the influence of the partial volume effect, Brain MR Image has the characteristics of overlapped gray, fuzzy region and typical weak boundary. The proposed fuzzy MRF model retains more detailed information in the gray fuzzy area. Classical MRF model has phenomenon of over segmentation in the gray fuzzy area.

FIGURE 1 Lena gray image

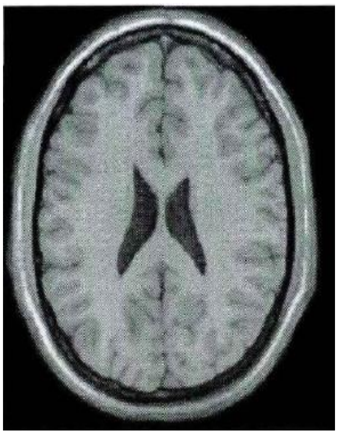

FIGURE 2 Brain MR Image

Figure 7 is original image of MR, reference segmentation effect of cerebral white matter is shown in Figure 8, segmentation effect of classical MRF is shown in Figure 9, segmentation effect of LCG-MRF [20] is shown in Figure 10, and segmentation effect of proposed algorithm is shown in Figure 11. Enlarged view of local area corresponding to Figure 9 is shown in Figure 12. Enlarged view of local area corresponding to Figure 10 is shown in Figure 13. Enlarged view of local area corresponding to Figure 11 is shown in Figure 14. It can be seen that more edge detail information is retained in the gray fuzzy area.

FIGURE 3 Effect of MRF

FIGURE 4 Effect of fuzzy MRF

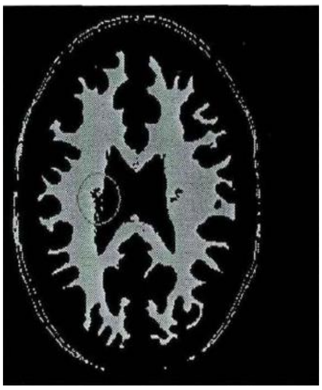

FIGURE 5 Effect of MRF

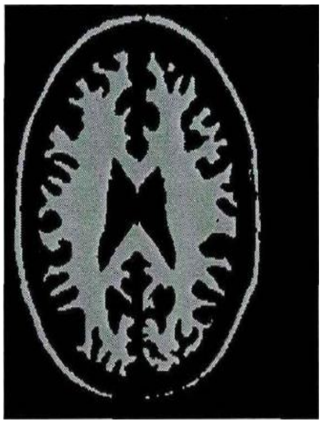

FIGURE 6 Effect of MRF

FIGURE 7 Original image of MR

FIGURE 8 Reference segmentation effect of cerebral white matter

FIGURE 9 Segmentation effect of classical MRF

FIGURE 10 Segmentation effect of LCG-MRF

FIGURE 11 Segmentation effect of proposed algorithm

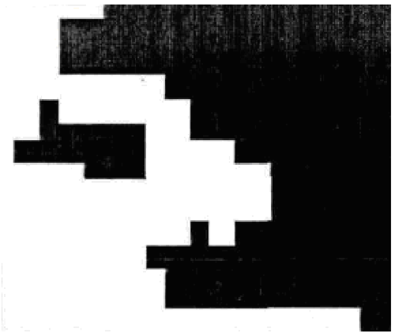

FIGURE 12 Enlarged view of local area corresponding to Figure 9

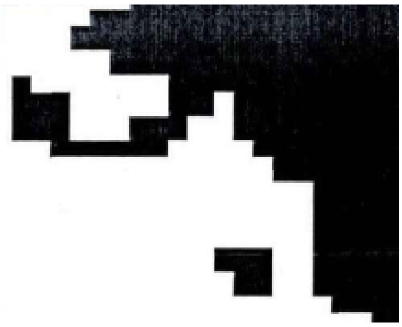

FIGURE 13 Enlarged view of local area corresponding to Figure 10

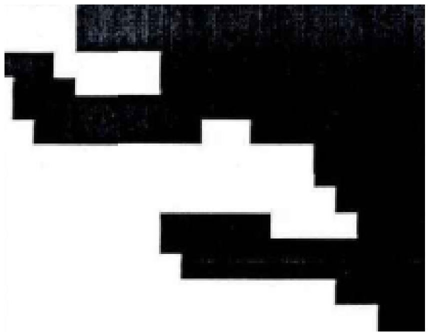

FIGURE 14 Enlarged view of local area corresponding to Figure 11

5 Conclusions

The fuzzy concept is introduced into traditional Markov random field, including membership establishment and detailed process. Experiments show that image segmentation algorithm based on proposed fuzzy MRF model has more precise image segmentation ability than the traditional segmentation algorithm based on MRF model.

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