An Improved Medical Image Registration Method

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Abstract

Image registration is a necessary pre-processing step before quantitative analysis of brain MR data. A novel variational optical flow approach for image registration is proposed in this paper. The advantages of our method are as follows. We coupled bias correction and optical flow image registration within the unified variational framework. We could recover the corrected target image through the estimated bias field. Experiments on synthetic and real brain images demonstrate the advantages of our method.

Keywords: *optical flow; bias field correction; medical image registration.*

1. Introduction

Image registration aims to geometrically match up two or more images of the same scene, taken at different times, from different viewpoints, or by different sensors, for structure localization, difference detection, and many other purposes. For brain MR image registration, many scholars proposed kinds of registration methods, such as mutual information based methods [1], intensity based methods [2]. The essence of image registration is how to obtain accurate displacement field between target images and registration images. The mutual information based methods have been extensively used for its accuracy and robustness. The methods can reduce the effect of the noise by using the region distribution information. However, these methods only use the intensity distribution information, which makes them sensitive to the bias field and cannot obtain accurate results on the edges.

The displacement field based on image registration is similar to the velocity field based on the optical field. Based on this idea, Palos and Hellier [3] have introduced the optical field to image registration. This method is based on the intensity information of the image, which can obtain more smoothed displacement. In order to obtain accurate results, many scholars have proposed many improved methods [4-7]. However, these improved models assumed that the optical flow field is continuous and smooth, which makes them hard to find the accurate edge information. Zach and Pock presented the dual method for small optical flow computation based on variational models [8], which allows the displacement field discontinuities in the edge regions and robust to varying intensities. However, it is sensitive to the bias field. In this paper, we propose an improved optical flow based registration and bias estimation coupled method.

2. Horn-Schunck Model

In order to solve ill-posed inverse problem of optical flow, Horn and Schunck firstly presented the global regularization item to obtain physically meaningful displacement fields. They proposed the following energy function:

$$E^{HS} = \int_{\Omega} \left(I_x u + I_y v + I_t\right)^2 + \alpha\left(|\nabla u|^2 + |\nabla v|^2\right) dxdy \tag{1}$$

Where ∇ is gradient operator, (I_x, I_y, I_t) is image I along x, y and t direction of image derivatives, α is a smooth coefficient. By minimizing Eq. (1), u and v can be solved as follows:

$$I_x\left(I_x u + I_y v + I_t\right) = \alpha \nabla^2 u \,,\; I_y\left(I_x u + I_y v + I_t\right) = \alpha \nabla^2 v \tag{2}$$

The HS model can obtain the smooth displacement fields, however, it only penalizes optical flow deviations in a quadratic way, which makes two major limitations. Firstly, it does not allow for discontinuities in the small displacement field, which makes the method failed to stop at the edge regions. Secondly, it does not take into account the intensity inhomogeneities information, which usually appeared in MR images.

3. Image Registration and Bias Field Correction Coupled Framework

The observed brain image Y is the product of the true brain image X generated by the underlying anatomy and spatially varying field factor B, and an additive noise N,

$$\mathrm{Y} = \mathrm{X} \times \mathrm{B} + \mathrm{N} \tag{3}$$

By taking the logarithmic transform of both sides, we do not consider the impact of noise and estimate the true image X as follows:

$$\log \mathrm{Y} = \log \mathrm{B} + \log \mathrm{X} \tag{4}$$

In order to reduce the effect of bias field, we coupled the bias field correction and image registration into a coupled variational framework:

$$E^{HS} = \int_{\Omega} \left(I_x u + I_y v + I_t\right)^2 + \alpha\left(|\nabla u|^2 + |\nabla v|^2\right) dxdy \tag{5}$$

Where $I(x, y, t)$ is the target image, $I(x+\Delta x, y+\Delta y, t+\Delta t)$ is registration image. In order to solve the bias field B, we take logarithmic transform:

$$E^{log\_BHS} = \int_{\Omega} \left(I_{\log}(x, y, t) - B - I_{\log}(x+\Delta x, y+\Delta y, t+\Delta t)\right)^2 dxdy \tag{6}$$

By using Taylor expansions $I_{\log}(x, y, t) - I_{\log}(x+\Delta x, y+\Delta y, t+\Delta t)$, without taking into about the impact of high order derivative. Eq. (6) can be written as:

$$I_{\log}(x+\Delta x, y+\Delta y, t+\Delta t) - I_{\log}(x, y, t) \approx f_x \frac{\Delta x}{\Delta t} + f_y \frac{\Delta y}{\Delta t} + f_t \tag{7}$$

where $\frac{\Delta x}{\Delta t} = u$, $\frac{\Delta y}{\Delta t} = v$,By incorporating Eq. (5) and Eq. (7) into Eq. (6) , Eq.(6) can be rewritten as follows:

$$E^{log\_BHS} = \int_{\Omega} \left(B - \left(I_x u + I_y v + I_t\right)\right)^2 dxdy \tag{8}$$

The optical flow field u and v can be calculated as :

$$\frac{\partial u}{\partial t} = -I_x\left(I_x u + I_y v + I_t - B\right),\quad \frac{\partial v}{\partial t} = -I_x\left(I_x u + I_y v + I_t - B\right) \tag{9}$$

By minimizing Eq.(8), the bias field B can be obtained as:

$$B = I_x u + I_y v + I_t \tag{10}$$

In order to obtain a smoothed bias field, we use a Gaussian filter to smooth B :

$$B = G_\sigma * B \tag{11}$$

Compared with traditional optical flow based model, the registration and bias correction are coupled into a unified variational framework. The bias correction can improve the accuracy of the registration and the registration can make the bias correction more accurate.

4. Experimental Results

Our algorithm is implemented in Matlab 7.0 on the Dell 2.0 GHz 1GB RAM computer. In each experiment, in order to calculate non-local kernel weight, we choose similar window size 2×2, the search window size 2×2 and similarity of adjustment parameters $h = 10$. The regular coefficients of HS model $\alpha = 10$ .We use mean, var and psnr to evaluate registration results, defined as follows:

(1)Mean

$$Mean = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(I_1(i,j) - I_2(i,j)\right)}{M\times N}$$

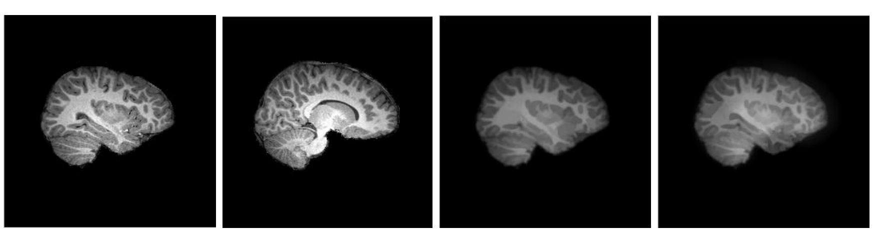
(2)Var

$$Var = \sqrt{\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(I_1(i,j) - I_2(i,j) - Mean\right)^2}{M\times N}}$$

(3) Psnr

$$PSNR = 10\lg\frac{\left(\max\left(I_1(i,j)\right)\right)^2 \times M\times N}{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(\left(I_1(i,j) - I_2(i,j)\right)^2\right)}$$

Where, I_1 is the target image, I_2 is registration image, (M , N) is the size of the image.



(a) (b) (c) (d)

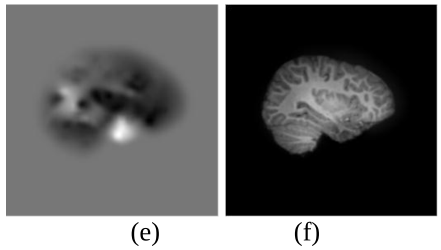


Figure 1. Registration and bias correction on a brain MR image. (a) the target image; (b)registration image; (c)result of the HS model; (d) result of our model; (e) estimated bias field ; (f) corrected target image.

Figure 1 shows the result on a brain MR image, which contain 3% noise, 20% bias field. Figure 1(a) is the target image. Figure 1(b) is the registration image. Figure 1(c) shows the result of the HS model, which iterates 1000 times. Analysis of registration result could be seen, which keeps the target image structure information better in contrast strong places, but makes registration result serious blurred in low contrast areas. Figure 1(d) shows the result of our model by iterated 1000 times. Compared to the HS model, The non-local image information could maintain image detail features and image consistency. Figure 1(e) and Figure 1(f) show bias field and the corrected image.

Figure 2 shows the result for true brain MR images, which significantly contain bias field, slender topology structure and point information. Figure 2(a) is the target image. Figure 2(b) is the registration image. Figure 2(c) shows the result of the HS model iterated 1000 times. The registration result has obvious vagueness at the image corners, and loses important information structure of the target image. Figure 2(d) shows the result of our model iterated 1000 times. Compared to the HS model, non-local regularization term remains important structural information such as the corner point of the target image and image consistency. Figure 2(e) and Figure 2(f) show bias field and the corrected target image.

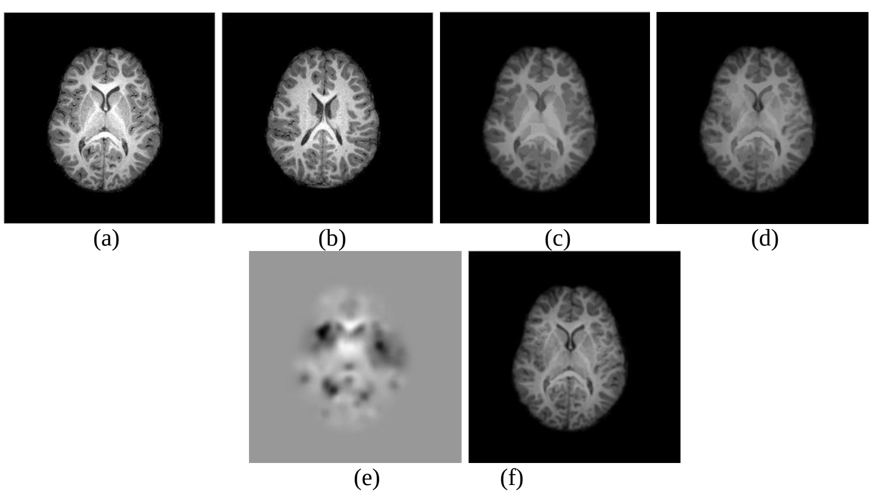


Figure 2. Registration and bias correction on a real brain MR image. (a)the target image; (b)registration image; (c)result of the HS model; (d) result of our model; (e) estimated bias field ; (f) corrected target image.

Table 1. Brain MR Image Registration Accuracy

	mean	var	psnr
HS model	0.7856	4.0123	36.3496
Our method	0.6841	2.2885	41.3462

Table 2. Brain MR Image Registration Accuracy

	mean	var	psnr
HS model	1.2543	5.5210	33.6022
Our method	1.0359	2.2885	38.0874

Registration accuracies of the HS model and our model are listed in Table 1 and Table 2 for Figure 1 and Figure 2. It can be seen that the mean and var values of our method are lower than HS model, the psnr values of our method are higher than HS model, which indicates that the registration result images obtained in our method are more accurate than HS model.

6. Conclusions

In this paper, we propose a new coupled variational model for brain MR image registration and bias field correction. We define energy functional with bias field correction, which mergers bias field correction and image registration into the unified framework to reduce the influence of bias field. Another advantage of our method is that it can obtain the corrected target image.

Acknowledgements

This work was supported by the National Nature Science Foundation of China 61003209, 61173072, 60973157 and University Science Research Project of Jiangsu Province 10KJB520012.

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