The Modulus of a Kind of Micro Equation

Shu Li
Hunan City University, Yiyang, 413000, China

Abstract: Based on the theory of differential equations, the differential equations of different classification, and image registration as the application object, the differential equations of different types of modeling finally, in different images in different differential equations in the simulation experiments, the simulation results show that the partial differential equation model of this paper in the extraction and recognition of image information in the debate, not only easy to read, but also more clearly and accurately, to achieve the effective registration.

Keywords: Image Feature,experiment, simulation

1. Introduction

Since the differential optical flow field model constructs regularization term starting from a smoothness constraint, so the evolution of image will inevitably result in blurring, the registration process is a process of iterations, therefore, the image with increasing number of iterations becomes smooth is an inevitable trend, results also reflect this phenomenon, Hom method is simple, fast, but can cause severe image blur; use edge enhanced model of WIckerton image registration, although able to keep an edge better than Hommodel, but because the model is proposed for static noise images, so that the model can not achieve accurate registration on the part which change violently. The model in this paper uses anisotropic diffusion as a flow-driven regularization term, according to the local image structures to control the evolution of the image, the character of the image can be maintained well; data item uses non-quadratic penalty function which effects on the brightness constant assumption, and make the model suitable for brightness changes caused by various motion, and it is more robust.

2. Self-adaption Anisotropic Registration and Solution based on Partial Differential Equations

In the differential optical flow field model, the adaptive penalty function is set on the application of optical flow model, to enhance the capability and robustness of the model, the formula of data items (1) into the partial differential fraction(2), get the energy function expression most are as follows:

$$\min Q(v) = \min\left\{\int_{\Omega}\left[\begin{matrix}(w_j a + w_l b + w_r)^2 + \\ \lambda\left(|\Delta a|^2 + |\Delta b|^2 + |\Delta r|^2\right)\end{matrix}\right] djdl\right\} \quad (1)$$

The equation corresponding to the energy functional is as follows:

$$\begin{cases}\left(\partial u_{jj} + \beta u_{ll}\right) - \frac{1}{\lambda}\psi\left(\left(\Delta w_j u + j_l\right)\right)\left(\Delta w_j u + j_l\right) d_j = 0 \\ \left(\partial u_{jj} + \beta u_{ll}\right) - \frac{1}{\lambda}\psi\left(\left(\Delta w_j u + j_l\right)\right)\left(\Delta w_j u + j_l\right) d_l = 0\end{cases} \quad (2)$$

$$\begin{cases}\partial_j u = \left(\partial u_{jj} + \beta u_{ll}\right) - \frac{1}{\lambda}\psi\left(\left(\Delta w_j u + j_l\right)\right)\left(\Delta w_j u + j_l\right) d_j = 0 \\ \partial_t v = \left(\partial u_{jj} + \beta u_{ll}\right) - \frac{1}{\lambda}\psi\left(\left(\Delta w_j u + j_l\right)\right)\left(\Delta w_j u + j_l\right) d_l = 0\end{cases} \quad (3)$$

3. Experimental

3.1. Brain MR Image Registration

Brain MR Chart is the most representative figure of optical flow field experiment, this experiment choose two brain MR images to be an image waiting registration and the reference image, in the case of constant illumination, choose Horn model and Lucas-Kanade model for comparative experiment. Horn model and model of this paper do iteration for 30 times respectively, window size of Lucas-Kanade model is 5, 5 layers iteration deformation between two images, and optical flow vectors shown in Figure 1, and then get the registration image which is shown in Figure 3.Figure 3 (e) shows the enlarged partial ventricle area in each image, you can see the registration and segmentation results more clearly of each model. The parameter value in table 3 further illustrates the effectiveness of our model to deal with complex images.
From the experimental results Figure 1 (c), we can see Horn model lead to image blurred quickly, and image edges and corners severely blurred and difficult to distinguish. Figure 1 (d) shows the registration results of Lucas-Kanade model, the upper edge of the image appears error message, verify that the model select window registration make image edge information loss, but the registration for the target image is superior than Horn model. The registration results of model presented in this paper (Figure 1 (e)) shows that this model is able to maintain image features, good attention to detail, and the closest to the reference image.

Figure.1. Registration Of Brain MR Image.

3.2. Different Pictures of Multi-modal Human Brain

The experiment realizes the registration of brain MR images of T1, T2 two modals and the segmentation of upper ventricles organization. Treat the clearer organization T1 picture as basic map (Figure 4(a)), and treat the fuzzy picture T2 to be segmented, the initial reference curve uses a known figure ventricle contour curve, as shown in 4 (b).Our model and the Wang model can overcome brightness inconsistencies, which can achieve the valid registration from T1to TZ.

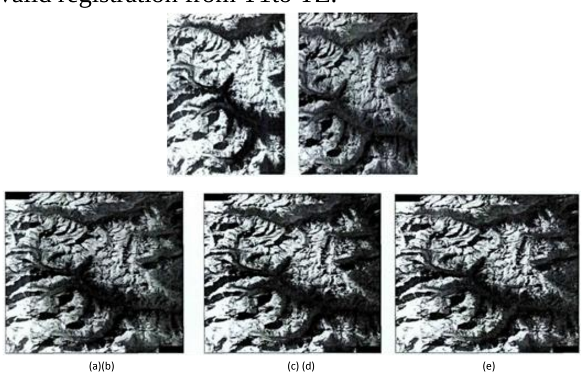

Figure.2. Experiment Result Of Multi-Modal Brain Figure MR

The data in Table 1 adequately describes the registration result of our model is significantly better than the Horn model and the Lucas-Kanade model, and is closest to the reference image, the peak signal to noise ratio is also the largest, indicating that this model has better strength. In addition, because Horn model is fuzzy seriously, especially the edge of error is too large, resulting alignment metric is very small; while Lucas-Kanade model appears false information on edge position which cause the alignment metric is small as well; our model has the characteristic of self-adaptive anisotropic, so it protect edges on the registration process avoid being lost.

Table.1. Results Evaluation Of Brain MR Image Registration.

model	*PSNR*	*Mean*	*Var*
Horn model	34.02	-0.12	31.24
Lucas-Kanade model	32.34	1.62	38.65
Proposed model	38.87	-009	9.23

Table 2 shows for brain MR images, this algorithm with other algorithms comparison of computing time. As can be seen by comparing, the computation time of this proposed algorithm is longer than the Horn model, than Lucas-Kanade model runs a short time. Mainly due to: 1) This article is a Horn model improvement in the data items and regular items on the design than the Horn model complexity; 2) Lu-cas-Kanade model is a hierarchical sub-window iteration, the window is smaller, the more stratified and more complex the model which is the Lucas-Kanade one of the drawbacks. As can be seen from Table 3, this model greatly improved the accuracy, computing time and did not slow down too much, indicating that the algorithm is effective.

Table.2. Computing Time Comparing Among Our Algorithm With Other Algorithms.

model	Image Size	Iterations	Computation time/s
Horn model	260×220	32	1.40031
Lucas-Kanade model	260×220	Sizeof window is 5.6 layer iteration	3.80625
Proposed model	260×220	32	1.56051

4. Conclusion

Curve can easily converge to local extrema or isolated edges in the evolutionary process, in order to solve these problems, many scholars have carried out improvement to the model, Cohen joined the balloon force in the model, to avoid the energy into the local extremum by expanding the boundary of the search range; Xu et al. The gradient vector flow snake model, the model approximation of the image gradient field, constructed a new force, to achieve the sag region segmentation, but the method of operation The complexity is very high; Menet et al for the snake model in the optimization process, the first-order derivative profile, two key data cannot be accurately calculated, using the B spline representation of contour line of B Sanke and A nit model; snake algorithm is proposed based on dynamic programming to solve the global optimal curve, the method the numerical stability, but also can increase the hard constraints, but also has the problem of high computational complexity.

References

[1] Lv, Z., Halawani, A., Feng, S., Li, H., &Réhman, S. U. (2014). Multimodal hand and foot gesture interaction for handheld devices. ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM), 11(1s), 10.

[2] Yizheng Chen, Fujian Tang, Yi Bao, Yan Tang, *Genda Chen. A Fe-C coated long period fiber grating sensor for corrosion induced mass loss measurement. Optics letters, 41(2016), pp. 2306-2309.

[3] Yang Du, Yizheng Chen, YiyangZhuang, Chen Zhu, Fujian Tang, *Jie Huang. Probing Nanostrain via a Mechanically Designed Optical Fiber Interferometer. IEEE Photonics Technology Letters, 29(2017), pp. 1348-1351.

[4] Weisen Pan, Shizhan Chen, ZhiyongFeng. Automatic Clustering of Social Tag using Community Detection. Applied Mathematics & Information Sciences, 2013, 7(2): 675-681.

[5] Yingyue Zhang, Qi Li, William J. Welsh, Prabhas V. Moghe, and Kathryn E. Uhrich, Micellar and Structural Stability of NanoscaleAmphiphilic Polymers: Implications for Anti-atherosclerotic Bioactivity, Biomaterials, 2016, 84, 230-240.