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Non-rigid image registration using local histogram-based features

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Abstract— **This paper proposes a new non-rigid image registration method based on the formulation of the Demons algorithm. The proposed method utilizes combined geometric moments of local histogram to form new feature images. It greatly improves the accuracy of the original Demons algorithm, which is easy to get trapped at local minima during optimization. The local histogram-based features are rotation invariant and can capture sufficient spatial image information. During the registration process, local histogram-based feature images are built to substitute the original intensity images. This can reduce the possibility of being trapped at local solutions, and consequently improve the registration accuracy. The experimental results on both the synthetic image and real MRI image show that the proposed method can achieve higher accuracy than the Demons algorithm especially when the images are noisy.**

I. INTRODUCTION

Non-rigid image registration has been vigorously studied in the recent decades. Many methods have been developed to improve the registration accuracy, such as different deformable models, various optimization methods, different constraints on transformation and so on. Generally speaking, non-rigid image registration methods can be divided into two categories: intensity-based methods [1][2][3] and feature-based methods [4][5]. A representative in the first category is the Demons algorithm proposed by Thirion [3]. It is derived from the optical flow model and is based on the principle of intensity conservation between images. In the Demons algorithm, there is no hard constraint on the transformation so that each pixel can have its own displacement. However, in real images, exact intensity matches do not necessarily imply good registration of the underlying anatomy. Thus, the intensity-based methods always suffer significantly from local minima of the energy function being optimized. On the other hand, feature-based registration methods utilize anatomical information in determining point correspondences. Therefore, they can suppress the effect of local minima. A typical example of the feature-based methods is the HAMMER algorithm [4]. It exploits the concept of attribute vector to match corresponding features between images, which makes the registration problem become a feature matching problem. The feature-based methods usually rely on a relatively small number of feature points to match the images. Thus, reliable feature selection has great impact on the accuracy of registration result.

In this paper, a new non-rigid registration method is proposed to make use of the advantages of these two kinds of methods, which utilizes the feature vectors of the whole image for an efficient matching task. The proposed method is grounded on the formulation of the Demons algorithm but utilizes local histogram-based features to find correspondences in the reference image and the moving image. The proposed method takes into account the underlying anatomy to build the feature image, so that it reduces the ambiguities in determining correspondences in the original Demons algorithm. Moreover, the computational load of calculating the local histogram-based feature image is quite small and negligible in the whole registration procedure. Experimental results show that the proposed method can achieve higher accuracy and is more robust against noise than the Demons algorithm.

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II. METHODOLOGY

Non-rigid image registration can be considered as an optimization problem that aims at finding the most desired displacement of each pixel to get an alignment of the reference image and the moving image. The Demons algorithm is one of the optimization procedures that works on the entire space of the displacement fields. It is inspired from the optical model with the basic hypothesis that the intensity of a moving object is constant with time. It relates the displacement of the moving image with respect to the reference image ($\boldsymbol{u}$) to the change in intensity between the reference image and the moving image ($m-s$) and the spatial derivative of intensity of the reference image (∇s) as follows,

$$\boldsymbol{u} \cdot \nabla s = m - s. \tag{1}$$

To make it numerically stable, it is approximated to give the following expression for displacement $\boldsymbol{u}$,

$$\boldsymbol{u} = \frac{(m-s)\,\nabla s}{|\nabla s|^2 + (m-s)^2}. \tag{2}$$

From this formula, it is obvious that the displacement is zero if the intensity values of the corresponding positions in the two images are the same ($m-s=0$), or the local gradient of the reference image is zero ($\nabla s = 0$). However, this formulation makes it easy to get into local minima if the images are contaminated by noise. To show this, Gaussian noise is added in the reference image and the moving image. Then the expression for $\boldsymbol{u}$ will become,

$$\boldsymbol{u} = \frac{(m-s+G_m-G_s)\,(\nabla s + \nabla G_s)}{|\nabla s + \nabla G_s|^2 + (m-s+G_m-G_s)^2}, \tag{3}$$

where G_s and G_m are, respectively, the Gaussian noise in the reference image and the moving image. In this situation, neither the match of the intensity of both images nor the

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zero local gradient of the reference image will lead to zero displacement, as there is always a residual term as follows,

$$\mathbf{R} = \frac{(G_m - G_s)(\nabla G_s)}{|\nabla G_s|^2 + (G_m - G_s)^2}. \tag{4}$$

This term reflects the influence of Gaussian noise on the accuracy of the Demons algorithm. It also reasons that the Demons algorithm is highly sensitive to local artifacts. In order to reduce the influence of this term, we compute a new feature image to substitute the original intensity image.

Local histogram of the intensity image is introduced to form the new feature image in our method. As it is stated in [5], features used for image matching are not necessarily very detailed, but must be robust to structural variations across individuals and also invariant to image rotation. Local histogram-based feature is a good candidate as it not only can meet the above requirement but also can be computed and matched efficiently. It can characterize the geometric features around each pixel, thus reducing the ambiguities in determining the correspondences in images. To build the local histogram-based feature image, the statistical feature is firstly extracted from each local histogram by calculating its geometric moments in the form as stated in Eq.(5):

$$M(x,y,p) = \sum_i i^p h(x,y,i), \tag{5}$$

where $h(x,y,i)$ is the ith component of the local histogram in the 2D position (x,y) and $M(x,y,p)$ is the pth order geometric moment of the local histogram. Low-order geometric moments (i.e., $p = 1,2$) are used in this algorithm, where first-order moment ($p = 1$) represents smoothed feature which suppresses noise, while second-order moment ($p = 2$) strengths the intensity contrast of the feature image. The first-order and second-order geometric moments are combined to form the local histogram-based feature image as follows,

$$A(x,y) = \sum_p M_{norm}(x,y,p), \tag{6}$$

where $M_{norm}(x,y,p)$ is the normalized pth order geometric moment of the local histogram.

Additionally, in the calculation of the local histogram $h(x,y)$, the choice of the radius of the local region depends on the noise level and resolution of the image. As an illustration, we compare the local histogram-based feature images with different radii (i.e., r=1,2,3) in Fig.1. As it is showed that larger region radius will help reduce intensity inhomogeneity and noise in the image, but will also reduce the details of the image. Therefore, we need to make a balance between preservation of details in the original image and removal of noise. The specific parameter choice will be stated in the experiments.

With the new feature images, we match the correspondent features that indicate the underlying anatomy instead of only intensity values of the reference image and the moving image. The displacement expression will become,

$$\boldsymbol{u} = \frac{(A_m - A_s)\nabla A_s}{|\nabla A_s|^2 + (A_m - A_s)^2}, \tag{7}$$

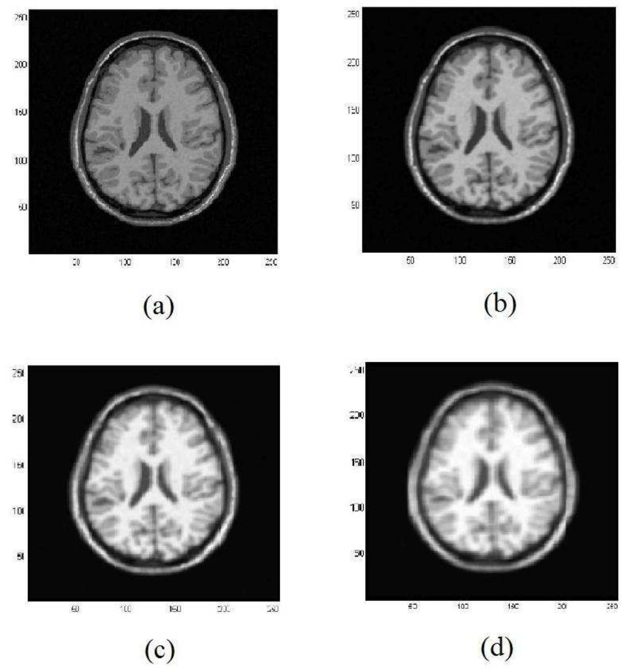

Fig. 1. Demonstration of local histogram-based feature images with different local region radii for histogram calculation. (a) the original MRI brain image. (b), (c) and (d) are respectively the local histogram-based feature images with r=1 (3×3 2D region), r=2 (5×5 2D region) and r=3 (7×7 2D region).

where A_s and A_m denote the local histogram-based feature image of the reference image and moving image respectively.

To illustrate the benefit of using local histogram-based feature image, we produced two registered 256×256 images with the intensity ranging from 0 to 1. The two images are the same MRI brain images, but one of which (Fig.2b) was contaminated by additive Gaussian noise with zero mean and 0.1 variance, as it is depicted in Figs.2a and 2b. According to Eq.(2), two registered images should have no displacement between them. However, due to the local artifacts (noise), the Demons will produce the residual displacement driving the originally registered moving image continue to deform. The residual displacement fields calculated with Eq.(4) in the original Demons algorithm and the proposed method are shown in Figs.2c and 2d. The sums of absolute residual displacement between the original images and the local histogram-based feature images are, respectively, 7.37×10^3 and 3.48×10^3. It indicates that the influence of residual displacement can be greatly reduced in the local histogram-based feature image.

The whole registration procedure is summarized as follows.

1. Calculate the geometric moments of local histogram of each pixel to form the local histogram-based feature image.

2. Compute the current displacement field based on Eq.(7) for each pixel in the feature image.

3. Regularize the displacement field with a Gaussian filter.

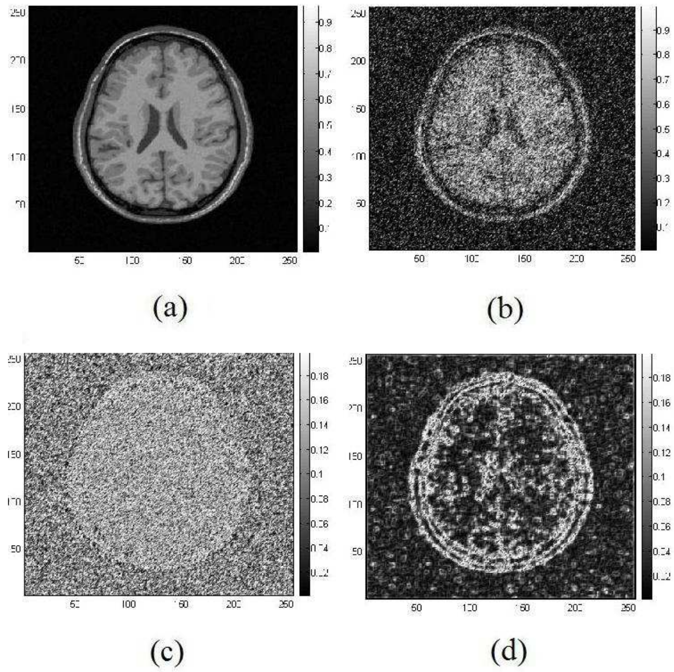

Fig. 2. (a) A 2D MRI brain image. (b) The noisy MRI brain image. (c) The residual displacement field between the original intensity images. (d) The residual displacement field between the local histogram-based feature images.

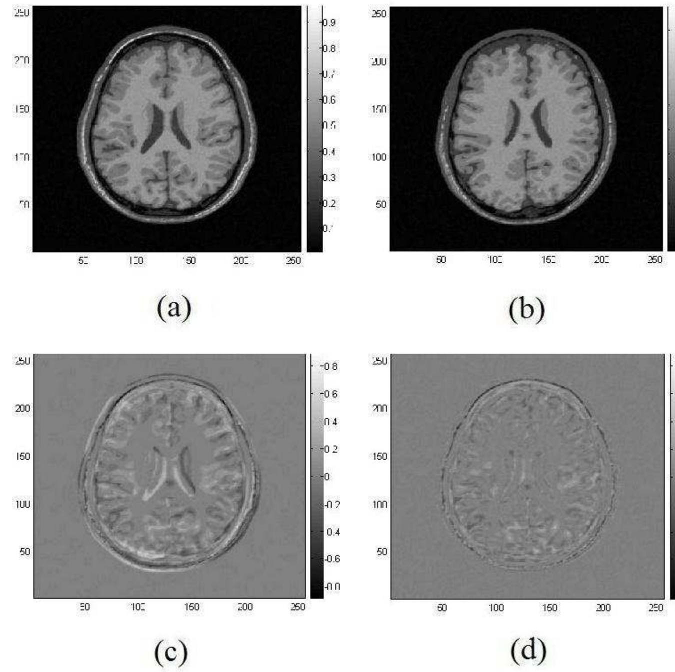

Fig. 3. (a) A 2D slice of the reference images. (b) A 2D slice of the moving images. (c) The difference before registration. (d) The difference after registration.

4. Use the current smoothed displacement field to update the transformation space.

5. Compute the new deformed moving image according to the transformation space.

6. Iterate step 2-5 until convergence.

III. Experimental result

A. Registration Accuracy

To compare the performance of the proposed method with the Demons algorithm, we have conducted 18 sets of inter-subject registration experiments based on the 3D T1 MRI brain image data obtained from the BrainWeb [6]. Among 19 subjects' brain data, subject 04 was used as reference images and the other 18 subjects were used as moving images. For Demons, we used the ITK implementation [7] with its default parameter. For the proposed method, radius for histogram calculation was set to 2, that is, $5 \times 5 \times 5$ local region for the 3D volume. The regularization parameter was set the same as the Demons.

Fig.3 shows the 2D slices obtained from 3D image volumes and it illustrates one registration result by using the proposed method. The quantitative evaluation method was based on the overlap of gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF) between the reference images and the transformed moving images. The overlap measure was defined as: $P = \frac{\sharp(A \cap B)}{\sharp(A \cup B)}$ [8], where A and B denote the regions of the two subjects that belong to a specific tissue classification. The segmentation ground truth was based on the segmentation label provided by the BrainWeb. The overlap measurements of WM, GM and CSF after applying the Demons algorithm and the proposed method are listed in Table 1. As it is shown in the table, the proposed method can achieve higher registration accuracy than the Demons algorithm in all sets of experiments.

B. Robustness to noise

To further test the proposed method's robustness to noise, we use an academic example that warps a 'C' to a circle as it is depicted in Figs.4a and 4b. We added Gaussian noise with zero mean and 0.1 variance to both images, and then applied the Demons algorithm and the proposed method. The results are given in Figs.4c and 4d. It is obviously seen from the results that the proposed method can achieve a better match to the circle than the Demons algorithm. Another example with noisy 3D MRI brain images is also shown. The original T1 MRI images of subject 04 and subject 38 were manually added with Gaussian noise with zero mean and 0.1 variance. Subject 04 was used as the reference images, and subject 38 as the moving images. The registration results shown in Table 2 testify our analysis that the proposed method outperforms the Demons when the images are noisy.

IV. Conclusion

In this paper, we have proposed a new non-rigid registration method aimed at improving the original Demons algorithm. In the proposed method, the local histogram-based feature image is formed based on the geometric moments of the histogram in the local region of each pixel. The feature

TABLE I

THE OVERLAP MEASUREMENTS OF WM, GM AND CSF IN 18 3D IMAGE REGISTRATION EXPERIMENTS ON THE BRAINWEB DATA

Subject number	Before registration			Demons algorithm			Proposed method		
	WM	GM	CSF	WM	GM	CSF	WM	GM	CSF
Subject06	0.4622	0.4556	0.2135	0.6101	0.6226	0.4581	0.7182	0.7101	0.5232
Subject18	0.4733	0.4877	0.2913	0.6097	0.6351	0.4947	0.7388	0.7308	0.5596
Subject20	0.4541	0.4566	0.2488	0.6005	0.6153	0.4763	0.6244	0.6771	0.5339
Subject38	0.4438	0.4602	0.2639	0.5865	0.6102	0.4468	0.7326	0.7167	0.5219
Subject41	0.4635	0.4638	0.2692	0.6009	0.6184	0.4557	0.7351	0.7209	0.5182
Subject42	0.4376	0.4566	0.2410	0.5857	0.6208	0.4724	0.7413	0.7207	0.5270
Subject43	0.4495	0.4201	0.2112	0.5900	0.5758	0.3980	0.7396	0.7018	0.4759
Subject44	0.4332	0.4336	0.2391	0.5701	0.5760	0.4383	0.6193	0.6171	0.5054
Subject45	0.4600	0.4516	0.2528	0.6181	0.6307	0.5009	0.6394	0.6839	0.5560
Subject46	0.4526	0.4457	0.2672	0.6008	0.6051	0.4627	0.7441	0.7172	0.5556
Subject47	0.4737	0.4583	0.2569	0.6199	0.6174	0.4605	0.7427	0.7207	0.5212
Subject48	0.4434	0.4318	0.2527	0.5813	0.5946	0.4943	0.7219	0.6943	0.5383
Subject49	0.4471	0.4042	0.2437	0.5890	0.5570	0.4265	0.5590	0.6224	0.4658
Subject50	0.4557	0.4461	0.2500	0.6002	0.6024	0.4289	0.7375	0.7093	0.4824
Subject51	0.4632	0.4705	0.2770	0.6080	0.6262	0.4853	0.6629	0.6921	0.5339
Subject52	0.4673	0.4640	0.2650	0.6256	0.6363	0.4928	0.7488	0.7246	0.5334
Subject53	0.4530	0.4433	0.2476	0.5981	0.5857	0.4087	0.7222	0.6777	0.4784
Subject54	0.4685	0.4650	0.2761	0.6103	0.6203	0.4767	0.7435	0.7212	0.5542

TABLE II

THE OVERLAP MEASUREMENTS FOR THE REGISTRATION BETWEEN NOISY SUBJECT04 AND SUBJECT38 DATA SETS

Subjects	Before registration			Demons algorithm			Proposed method		
	WM	GM	CSF	WM	GM	CSF	WM	GM	CSF
Noisy subjects	0.4438	0.4602	0.2639	0.5040	0.5366	0.3899	0.7170	0.7041	0.5146

image is then combined with the Demons principle to realize image registration. The proposed method can help overcome intensity inhomogeneity and noise in the image, further reducing local minima in the optimization. The analysis and experimental results show that the proposed method can give higher registration accuracy even with high level of noise.

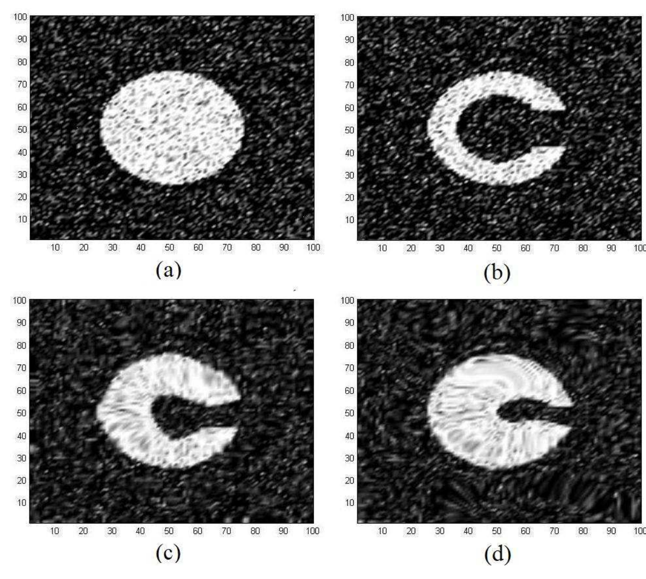

Fig. 4. Demonstration of the proposed method's robustness to noise. (a) and (b) are respectively the noisy reference image and the moving image. (c) is the deformed moving image by applying the Demons algorithm. (d) is the deformed moving image by using the proposed method.

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