An Effective Non-rigid Registration Approach for Ultrasound Image Based On “Demons” Algorithm

Yan Liu · H. D. Cheng · Jianhua Huang ·
Yingtao Zhang · Xianglong Tang · Jiawei Tian

Published online: 10 October 2012
© Society for Imaging Informatics in Medicine 2012

Abstract Medical image registration is an important component of computer-aided diagnosis system in diagnostics, therapy planning, and guidance of surgery. Because of its low signal/noise ratio (SNR), ultrasound (US) image registration is a difficult task. In this paper, a fully automatic non-rigid image registration algorithm based on demons algorithm is proposed for registration of ultrasound images. In the proposed method, an “inertia force” derived from the local motion trend of pixels in a Moore neighborhood system is produced and integrated into optical flow equation to estimate the demons force, which is helpful to handle the speckle noise and preserve the geometric continuity of US images. In the experiment, a series of US images and several similarity measure metrics are utilized for evaluating the performance. The experimental results demonstrate that the proposed method can register ultrasound images efficiently, robust to noise, quickly and automatically.

Key words Computer-aided diagnosis (CAD) · Image registration · Ultrasound image · Inertia force

Y. Liu · H. D. Cheng · J. Huang · Y. Zhang · X. Tang
School of Computer Science and Technology,
Harbin Institute of Technology,
Harbin, No. 92, Xidazhi Street,
Harbin 150001, People’s Republic of China

Y. Liu
College of Science, Harbin Institute of Technology,
Harbin, No. 92, Xidazhi Street,
Harbin 150001, People’s Republic of China

H. D. Cheng (✉)
Department of Computer Science, Utah State University,
Logan, UT 84322, USA
e-mail: hengda.Cheng@usu.edu

J. Tian
Second Affiliated Hospital of Harbin Medical University,
Harbin, China

Introduction

Breast cancer is one of the most common cancers and affects women’s health seriously [1]. Due to daily physiological changes or clinical factors, the deformation of soft tissues and/or velocities could be caused in different phase during the normal course of treatments. In medical applications, image registration can be used to monitor tumor development or treatment over time, to make an operation plan, or to compare images from different subjects [2]. It could also be used for spatial compounding of images to improve image quality and contrast. Typically, registration algorithms can be divided into rigid registration using linear transformation (translation, rotation, and scaling) and non-rigid registration using nonlinear transformation to compensate for the displacement and the pattern variation of the object. The physical characteristics of soft tissue changes in organs or tissues determine that the non-rigid registration is more suitable for medical images. Previous deformable image registration algorithms focused on the registration of medical images including magnetic resonance imaging [3], computed X-ray tomography [4–6], positron emission tomography [7, 8], and single photon emission computed tomography [9–11]. Comparing to above imaging types, ultrasound (US) imaging is more prevalent and effective in early detection of breast cancer because of its noninvasive, practically harmless, and cost-effective nature [12]. However, the automatic registration of breast ultrasound image (BUS) was not well developed due to its low signal-to-noise ratio (SNR) and high speckle noise caused by artifacts and attenuation.

Traditional image registration algorithms can be categorized into two classes: feature-based algorithms and intensity-based algorithms. Several methods for US image registration have been developed [13–15]. However, these methods still have problems in dealing with BUS images. Feature-based algorithm is useful for processing noisy images by matching the features such as geometric features

and local texture features in the deformed image with that in the static image. However, the potential error of feature extraction may be carried over into the deformable image registration process because of the changes in the location, shape, size, and texture of lesions caused by the physiological changes and the stress of ultrasound probe. Besides, extra time for preprocessing and extracting features is needed. Intensity-based algorithms can use pixel (or voxel) information directly, but the registration methods utilizing intensity-based algorithms such as SSD (sum of squared intensity differences) and SAD (sum of absolute differences) are very sensitive to the change of intensities, such as noise [16]. Although some methods used a smooth operation to suppress noise during registration process [17–19], the trade-off between noise and feature preserving is a dilemma. Therefore, an effective non-rigid image registration method for BUS image registration is needed.

Demons algorithm is quite popular for non-rigid image registration because of its linear computational complexity and easiness of implementation [17]. In this paper, a fully automatic non-rigid image registration method based on demons algorithm is proposed for US images. To handle low SNR and preserve the geometric continuity, a new force is proposed and added to the optical flow equation to estimate the demons force. Demons at any point in the image space will produce not only a force derived from the local gradient information, but also produce an “inertia force” originating from the motion trend of pixels in a Moore neighborhood system, which allows the moving image to diffuse into the corresponding static image more suitably; especially, when the gradient on US image is unsteady. In the experiment, a series of US images and three statistical similarity measure metrics: sum of squared difference, correlation coefficient, and normalized mutual information are employed for evaluating the performance. The experimental results demonstrate that the proposed method can register US images efficiently, robust to noise, quickly and automatically.

Methods and Materials

Data Acquisition

There are 60 BUS videos in our database collected by 2nd Affiliated Hospital of Harbin Medical University using HITACHI Vision 900 system (Hitachi Medical System, Tokyo, Japan) equipped with a liner probe having central frequency of 6–13 MHz. The cases were obtained from February 2008 to March 2011, and all the classes of the images were confirmed by surgery, pathological examinations, or biopsy. Special attention is paid to protect the privacy of the patients. The length of the US video has 2–

7 s with 10 fps. For each pair of consecutive frames in a BUS image sequence, the previous frame is used as a static reference image S while the following frame is used as the moving image M which is deformed according to S .

The Proposed Method

The original demons algorithm used the local gradient information from a static reference image S to determine the demons force required to deform the moving image M . In the original demons algorithm, the optical flow equation is used to estimate the demons force. For a given point p , let $S(p)$ be the intensity in S and $M(p)$ be the intensity in M . Then the estimated demons force f_0 required for $M(p)$ to match the corresponding point in S is given as:

$$f_0 = \frac{(M(p) - S(p)) \vec{\nabla} S(p)}{|\vec{\nabla} S(p)|^2 + (M(p) - S(p))^2} \quad (1)$$

In Eq. (1), $\vec{\nabla} S(p)$ is the internal force $\vec{f}_a^s(p)$ originating from the local gradient information, representing the relationship of neighboring pixels of the static reference image. $M(p) - S(p)$ is an external force representing the differential interaction between the static images and the moving images. In original demons, $M(p)$ will be pushed according to $\vec{\nabla} S(p)$ if $S(p) < M(p)$ or pulled according to $-\vec{\nabla} S(p)$ if $S(p) > M(p)$. Equation (1) is calculated iteratively to estimate the demons force until the demons converges to a stable configuration. However, due to high speckle noise, the local gradient information on static image is unsteady and Eq. (1) may not be efficient. Figure 1 is an example of registration by using the original demons algorithm [17]. The right part in Figure 1(a) is the registration result of the left part, and the position of the yellow marked moving pixel $M(p)$ is matched well with the corresponding point in the static image. The same force is applied to the yellow marked moving pixel $M(p)$ in Figure 1(b). However, it is seen that due to unsteady gradient information, the yellow marked $M(p)$ is pushed to an unsuitable position by the original demons force.

In addition, previous demons-based algorithms usually suppress the noise and preserve the geometric continuity of the deformed image by using a Gaussian filter with a variance of σ [2] as a smooth operation to regularize the deformation field [17–19]. However, if σ is too small, the noise may not be suppressed efficiently. If σ is too large, the detail of image may be degraded greatly. Some works estimated the demons force by adding different kinds of extra force to optical flow Eq. 1 [8, 19]. However, since the demons force that drives the deformation is inefficiently taken from the local gradient information only, these methods still have the problems in dealing with low SNR.

Fig. 1 An example of original demons. **a** Original demons force pushes $M(p)$ to a suitable position. **b** Original demons force pushes $M(p)$ to a unsuitable position

Since the demons force derived from the unsteady gradient information of US image is unsteady, in this study, an extra force is added to the optical flow equation to estimate the new demons force. The proposed method is based on a fundamental law of inertia: an object has the tendency to resist any change in its motion. Assuming a moving “car” encounters a “small pit” and a “large pit,” it may cross over the small pit by its inertia and stay in its original movement direction. However, for the large pit, its momentum will be decreased greatly, and it may even fall into the large pit. Similarly, the pixel in moving image is like a “car,” while the speckle noise and boundary region in static image is considered as a “pit.” Figure 2(a) is a US image marked with a dashed line. The speckle noise in the red circle marked region in Figure 2(b) is like a “small pit,” and the boundary region in the blue circle marked region in Figure 2(b) is like a “large pit.” By adding an extra force, the moving pixel can be pushed across the speckle noise point but stopped at the boundary point. Hence, in this paper, we call the extra force as “inertia force.”

By analyzing the diffusion principle of demons algorithm, we find that the motion of pixels driven by the demons force is essentially based on the relationship of

Fig. 2 The “Small pit” and the “large pit” in the US image. **a** Original US image marked with a dashed line. **b** Corresponding intensities of the dashed line.

pixels, such as intensity difference. Accordingly, in proposed diffusing model, the motion trend of each pixel is derived from the intensity variation information of pixels in

Fig. 3 An example of pixels’ motion in proposed method by applying “inertia” force

its local neighborhood system. The inertia force of the static image $f_b^s(p)$ is given as:

$$f_b^s(p) = \text{mean} \left(\sum_p^{p+r} (S^t(p)) - \sum_p^{p-r} (S^t(p)) \right) \quad (2)$$

where t is the iteration number and r is the radius size of Moore neighborhood system [20]. The parameter r for determining the scope of Moore neighborhood system should be appropriately selected. If r is too small, the local intensity variation information of pixels may be affected by the speckle noise greatly; if r is too large, intensities of different regions may be wrongly included. Assuming that diffusion is bi-directional,

both $\vec{f}_a^s(p)$ and $\vec{f}_b^s(p)$ are acting along a straight line, then the proposed internal force derived from the static reference image f_e^s is given based on the resultant force formula:

$$\vec{f}_e^s(p) = \vec{f}_a^s(p) + \vec{f}_b^s(p) \quad (3)$$

Another equation, similar to Eq. (3), is used to define an active force f_e^m of the moving image:

$$\vec{f}_e^m(p) = \vec{f}_a^m(p) + \vec{f}_b^m(p) \quad (4)$$

where $\vec{f}_a^m(p)$ is the internal force originating from the local gradient information and $\vec{f}_b^m(p)$ is the corresponding inertia

Fig. 4 The registration result of AD method and proposed method. **a** Static reference image. **b** Moving image. **c** The registration result of AD model. **d** The registration result of WD model. **e** The registration result the proposed method. **f** The difference between static reference and moving images. **g** The difference between static reference image

and the registered image derived from **b** using AD method. **h** The difference between static reference image and the registered image derived from **b** using WD method. **i** The difference between static reference and the registered image derived from **b** using proposed method

force at point p of the moving image, respectively. Based on f_e^s and f_e^m , the total force $\vec{f}$ at point p is given as:

$$\vec{f} = \frac{(M(p) - S(p)) \cdot (\vec{f}_e^m(p) + \vec{f}_e^s(p))}{|\vec{f}_e^m(p) + \vec{f}_e^s(p)|^2 + (M(p) - S(p))^2} \quad (5)$$

In Eq. (5), the term $\vec{f}_e^m(p) + \vec{f}_e^s(p)$ gives each pixel $M(p)$ with a resultant force to estimate the new demons force iteratively. The estimated new demons force of the proposed method is based on the following ideas. If $\vec{f}_b^s(p)$ has the same action direction of $\vec{f}_a^s(p)$, $M(p)$ will remain in the movement direction with $\vec{f}_a^s(p)$. If $\vec{f}_b^s(p)$ has the opposite

direction of $\vec{f}_a^s(p)$, after several iterations, the action direction of $\vec{f}_a^s(p)$ will be modified by $\vec{f}_b^s(p)$ gradually. Finally, $M(p)$ can be pushed to the expect direction (see Fig. 3).

Evaluation Methods

To evaluate the performance of registration result, three similarity measure metrics: sum of squared difference (SSD), correlation coefficient (CC), and normalized mutual information (NMI) are utilized for statistical evaluation. SSD is one of the most prevalent similarity measurement calculated by subtracting the intensities of pixels between two images within a squared neighborhood. Let $D(i,j)$ be the pixel set of registered image D and $S(i,j)$ be the pixel set of corresponding static image S , then the SSD is defined as:

$$\text{SSD} = \frac{\sqrt{\sum_{i=1}^m \sum_{j=1}^n (S(i,j) - D(i,j))^2}}{m \times n} \quad (6)$$

where i and j are the coordinate of pixels in S and D , respectively. When the SSD ratio is lower, the deformed image is more similar to the corresponding static image.

Correlation coefficient measures how well two corresponding images are linearly related, describing the degree of overlapping areas between two images at different time [21]. The correlation coefficient has the value $\text{CC}=1$ if the two images are absolutely identical, and the performance of registration is the best. $\text{CC}=0$ if two images are uncorrelated.

$$\text{CC} = \frac{\sum_{S(i,j)} \sum_{D(i,j)} (S(i,j) - \bar{S}(i,j)) (D(i,j) - \bar{D}(i,j))}{\sqrt{\sum_{S(i,j)} (S(i,j) - \bar{S}(i,j))^2} \cdot \sqrt{\sum_{D(i,j)} (D(i,j) - \bar{D}(i,j))^2}} \quad (7)$$

where $\bar{S}(i,j)$ is the average of $S(i,j)$ and $\bar{D}(i,j)$ is the average of $D(i,j)$.

Normalized mutual information (NMI) can be quantitatively considered as a measure of how well one image matching another [22]. The normalized mutual information is calculated by the joint entropy of the intensities between the two images to be registered. The NMI is defined as:

$$\text{NMI} = \frac{MI - \min(MI)}{\max(MI) - \min(MI)} \quad (8)$$

where

$$MI = H(S) + H(D) - H(S, D) \quad (9)$$

where $H(S) = \sum_{x_S \in S} P(x_S) \log P(x_S)$ is the entropy of image S ,

Fig. 4 (continued)

$H(D) = \sum_{x_D \in D} P(x_D) \log P(x_D)$ is the entropy of image D , and $H(S, D) = \sum_{x_S \in S} \sum_{x_D \in D} P(x_S, x_D) \log P(x_S, x_D)$ is the joint entropy of image S and D , where $P(x_S)$ and $P(x_D)$ are the probability distribution function of S and D , and $P(x_S, x_D)$ is the joint probability distribution function of S and D , respectively.

Results

For studying the characteristic of the inertia force, the proposed method is applied to US images first and two other non-rigid image registration methods: active demons algorithm (AD) and fast inverse consistent demons algorithm (CD) are utilized for comparison [18, 19]. In AD model, an “active force” derived from the local gradient information of moving image was added besides the passive force (fo) to estimate the demons force. With the gradient information in both static image and moving image that were synchronously considered, the AD model can converge more quickly and require fewer iterations than original demons algorithm.

The CD model proposed a “fast inverse consistent demons” algorithm in which both static image moving image were symmetrically deformed toward one another in each iteration. The optical flow computations in both AD model and CD model were followed with a smooth operation using Gaussian filter with a variance $\sigma^2=1$.

In the proposed method, parameter r for determining the scope of Moore neighborhood system is selected according to the registration performance tested with different r values. By the experiment, we found that when r was set to 3; the proposed method can achieve a best performance and it was selected as the radius of Moore neighborhood system of the proposed method.

Figure 4(a) is a static reference US image; Figure 4(b) is the corresponding moving image captured from the same video after 0.1 s. By using the AD model, the registration result is shown in Figure 4(c). It is seen that there are trivial regions generated, some areas do not converge suitably appearing in a mastic pattern. The AD model gets a poor result because the estimated demons force is calculated from the local gradient information of the static/moving images only. Since the local gradient information in US image is unsteady, the pixel in the moving image may be pushed to a

Fig. 5 SSD ratio comparisons between three methods

Fig. 6 SSD between the static image and the deformed image as a function of iteration number for three methods

wrong direction towards the corresponding pixel in the static image, leading trivial regions or mastic pattern and getting a poor registration result. In addition, after several smooth operations with Gaussian filtering, the detail of the original moving image is damaged and the corresponding deformed image is quite fuzzy. The same problem happened to the CD model, it is seen that the registration result generated in Figure 4(d) does not match the static image well. The difference between the static reference image, moving image, and the deformed images generated by using AD, CD, and proposed method is shown in Figure 4(f–i), respectively. Comparing to AD and CD method, the registration result of the proposed method is more suitable, and the detail and the geometric continuity of the deformed image are preserved well.

Table 1 Overall performance of different methods

Method	Mean SSD	Mean CC	Mean NMI
The AD model	0.77	0.71	0.69
The CD model	0.67	0.75	0.68
The proposed method	0.46	0.90	0.81

For validating the registration performance of proposed method quantitatively, for each US case, the SSD between the static image and its corresponding moving image (SSD_{sm}) and the SSD between the static image and corresponding deformed image (SSD_{dm}) generated by using different methods are calculated. In this paper, $PSD_{sm} = SSD_{sm}/SSD_{sm}$ are normalized to 1 as the similarity criterion, $PSD = SSD_{dm}/SSD_{sm}$ is used for statistical evaluation between SSD_{sm} and SSD_{dm} . $PSD < 1$ means the deformed image is closer to the static image than the original moving image, while PSD close to 0 denotes that the deformed image and the static image are more similar, meaning the registration is more efficient. The statistical evaluations of two methods are shown in Figure 5.

Table 2 The registration performances of three methods applied to the US images adding the white Gaussian noise

Mean SSD	$\sigma^2=0.01$	$\sigma^2=0.02$	$\sigma^2=0.03$
The AD model	0.80	0.81	0.85
The CD model	0.78	0.81	0.83
The proposed method	0.48	0.48	0.49

From Figure 5, it is seen that after registration, the PSD ratio of AD model and CD model is carried out in PSD1 and PSD2, respectively. It is seen that the PSD ratio of proposed method (PSD3) is much lower than that of two other methods, and the curve distribution is also much steadier. This demonstrates that the registration result of the proposed method is more reliable.

Another statistical evaluation of the efficiency of different methods is also carried out with SSD. In this experiment, three methods are set to 30 iterations, and the SSDs of different methods for each iteration are calculated. It is seen from Figure 6 that the proposed method can converge more quickly, and the SSD of proposed method is much lower than that of two other methods. This demonstrates the proposed method can converge more quickly and needs less iteration to achieve a better performance.

For evaluating the overall performance of different methods, AD model, CD model, and the proposed method are applied to the same images for comparison. The statistical evaluations for three methods with above-mentioned similarity metrics are listed in Table 1. From Table 1, it is seen that the SSD ratio of proposed method is lower, while the CC ratio and NMI ratio are higher than that of two other methods. This demonstrates that the registration result of proposed method is more accurate.

Table 2 is the registration performances of three methods applied to the US images in our database adding the white Gaussian noise with variances $\sigma^2=0.01$, $\sigma^2=0.02$, and $\sigma^2=0.03$, respectively. It is seen that to the cases with high speckle noise, the performances of AD model and CD model are degraded greatly. Comparing to them, the proposed method still achieves a much lower SSD ratio than that of two other methods. This demonstrates that the proposed method is robust to the noise.

The proposed method produces better result for the following reasons: (1) By employing the inertia force, the internal force derived from the unsteady gradient information of US image can be fixed during iteration progress; thus the proposed method is insensitive to noise. (2) The proposed inertia force is potentially a smooth operation by considering the local intensity distribution information of Moore neighborhood system, thus, the geometric continuity of image can be preserved as well. Different to other methods, the smooth function in proposed method is potentially integrated into the demons force during registration process; therefore, the image detail can also be preserved.

The processing speeds of the methods are also studied. All of methods are performed on a Core2 PC with 4 GB RAM using MATLAB. The computing time to perform a registration depends on the size of the original static reference US image and the resemblance of the moving image relative to the corresponding static reference image. For a typical 240×400 US image, the AD model needs about

135 s to complete the registration, while the CD model needs nearly 90 s. The proposed method needs less time to reach the convergence (around 70 s) because there is no smoothing operation utilized.

Discussion and Conclusion

In this paper, we implement an effective non-rigid image registration method using a novel demons algorithm for US image registration. To handle low SNR, the proposed method adds an inertia force to optical flow equation to estimate the demons force, which can make the moving image diffuse into the corresponding static images more suitably. Comparing to other methods based on demons algorithm, the proposed method can keep the image geometric continuity well while preserve the image detail. The experimental results demonstrate that the proposed method can register the image efficiently quickly and automatically, and is robust to noise.

Acknowledgments Financial support from the National Nature Science Foundation of China (NSFC) greatly appreciated; Grant numbers: 81071216, 61100097.

References

1. Jemal A, Siegel R, Xu J, Ward E: "Cancer statistics 2010", CA: A Cancer Journal for Clinicians, 2010.
2. Maintz JB, Viergever MA: A survey of medical image registration. *Medical Image Analysis* 2(1):1–36, 1998
3. Rogelj P, Lovacic S: Symmetric image registration. *SPIE-Medical Imaging: Image Processing*, 334, 2003.
4. Ji JX, Pan H, Liang ZP: Further analysis of interpolation effects in mutual information-based image registration. *IEEE Trans Med Imaging* 22(9):1131–1140, 2003
5. Penney GP, Schnabel JA, Rueckert D, Viergever MA, Niessen WJ: Registration-based interpolation. *IEEE Trans Med Imaging* 23(7):922–926, 2004
6. Chen HM, Varshney PK: Mutual information-based CT-MR brain image registration using generalized partial volume joint histogram estimation *IEEE Trans. Med Imaging* 22(9):1111–1119, 2003
7. Woods RP, Cherry SR, Mazziotta JC: Rapid automated algorithm for aligning and reslicing PET images. *J Comput Assist Tomogr* 16(4):620–633, 1992
8. Woods RP, Mazziotta JC, Cherry SR: MRI-PET registration with automated algorithm. *J Comput Assist Tomogr* 17(4):536–546, 1993
9. Brown LG: A survey of image registration techniques. *ACM Computing Surveys*, 326–376, 1992.
10. Hill DL, Batchelor PG, Holden M, Hawkes DJ: Medical image registration. *Phys Med Bio* 46(3):1–45, 2001
11. Pluim JP, Maintz JB, Viergever MA: Mutual-information-based registration of medical images: a survey. *IEEE Trans Med Imaging* 22(8):986–1004, 2003
12. Cheng HD, Shan J, Ju W, Guo YH, Zhang L: Automated breast cancer detection and classification using ultrasound images: a survey. *Pattern Recog* 43:299–317, 2010

13. Woo JH, Hong BW, Hu CH, Shung KK, Kuo CC, Slomka PJ: Non-rigid ultrasound image registration based on intensity and local phase information. *J Sign Process Syst* 54:33–43, 2009
14. Chang RF, Chen CJ, Etsuo T, Kuo CM, Chen DR: Image stitching and computer-aided diagnosis for whole breast ultrasound image. *Proceedings of The 20th International Congress and Exhibition on Computer Assisted Radiology and Surgery*, Osaka, Japan, 2006.
15. Chang RF, Chen CJ, Etsuo T, Chen DR, Chou YH: Image stitching for three-pass whole breast ultrasound. *Proceedings of the 2006 SPIE Medical Imaging Symposium*, San Diego, CA, 2006.
16. Chen CJ, Chang RF, Moon WK, Chen DR, Wu HK: 2-D ultrasound strain images for breast cancer diagnosis using nonrigid subregion registration. *Ultrasound Med Bio* 32(6):837–846, 2006
17. Thirion JP: Image matching as a diffusion process: an analogy with Maxwell's demons. *Med Image Anal* 2:243–260, 1998
18. Wang H, Dong L, Daniel DJ, Mohan R, Garden AS, Ang KK, Kuban DA, Bonnen M, Chang JY, Cheung R: Validation of an accelerated 'demons' algorithm for deformable image registration in radiation therapy. *Phys Med Biol* 50:2887–2905, 2005
19. Yang D, Low DA, Deasy JO, Naqa IE: A fast inverse consistent deformable image registration method based on symmetric optical flow computation. *Phys Med Biol* 53:6143–6165, 2008
20. Vezhnevets V, Konouchine V: "Grow cut" - interactive multi-label N-D image segmentation by cellular automata. *Proc. of Graphicon*. 150–156, 2005.
21. Jeongtae K, Jeffrey AF: Image registration using robust correlation. *IEEE Trans Med Imaging* 23(11):1430–1443, 2004
22. Paninski L: Estimation of entropy and mutual information. *Neural Comput* 15:1191–1253, 2003