International Journal of Medical, Medicine and Health Sciences
ISSN: 2517-9969
Vol:5, No:2, 2011

Efficient Feature-Based Registration for CT-MR Images Based on NSCT and PSO

Nemir Al-Azzawi, Harsa A. Mat Sakim, Wan Ahmed K. Wan Abdullah and Yasmin Mohd Yacob

***Abstract*—**Feature-based registration is an effective technique for clinical use, because it can greatly reduce computational costs. However, this technique, which estimates the transformation by using feature points extracted from two images, may cause misalignments. To handle with this limitation, we propose to extract the salient edges and extracted control points (CP) of medical images by using efficiency of multiresolution representation of data nonsubsampled contourlet transform (NSCT) that finds the best feature points. The MR images were first decomposed using the NSCT, and then Edge and CP were extracted from bandpass directional subband of NSCT coefficients and some proposed rules. After edge and CP extraction, mutual information was adopted for the registration of feature points and translation parameters are calculated by using particle swarm optimization (PSO). The experimental results showed that the proposed method produces totally accurate performance for registration medical CT-MR images.

***Keywords*—**Feature-based registration; Mutual Information; Nonsubsampled contourlet transform (NSCT); Particle swarm optimization (PSO).

I. INTRODUCTION

THE goal of image registration is to find an optimal geometric transformation between corresponding image data [1], where the criteria for optimality depends on specific application. For example, in neurosurgery it is currently helpful to identify tumors with magnetic resonance images (MRI); however the established stereotaxy technology uses computed tomography (CT) images. Being able to register these two modalities allows one to transfer the coordinates of tumors from the MR images into the CT stereotaxy. Previous work on medical image registration can be characterized based on the used image information into intensity-based methods and feature-based [2]. The first class utilizes image intensity to estimate the parameters of a transformation between two images using an approach involving all pixels of the image.

In contrast, the second class does not work directly with image intensity values and rely on establishing feature correspondence between the two images. The feature-based matching algorithm may be performed by iterative closest point (ICP) algorithms [3] or by optimizing deformable models [4]. This methods, firstly uses feature matching techniques to determine corresponding feature pairs from the two images, and then compute the geometric transformation relating them.

The accuracy of registration algorithm is consequently affected by the segmentation and feature extraction algorithms [2]. Researching and exploring more accurate and faster registration algorithm is a very important domain. The main advantage of feature-based method, where a matching algorithm is sought between corresponding objects within the images, is approximately invariance for the intensity characteristics of the pixels. This method is sensitive to the error of feature extraction and matching [5]. Wavelet bases are commonly used to generate features for image registration to handle the accurate feature extraction [6-7].

Nonsubsampled contourlet transform (NSCT) is able to capture significant image features across spatial and directional resolutions [8-9]. It is ordinary to ask whether mutual information can play a comparable role in feature-based matching as well. Given that both MR and CT are informative of the same underlying anatomy, there will be mutual information between the MR image and the CT image. Rangarajan [10] demonstrates that mutual information can be utilized to parameterize and solve the correspondence problem in feature-based registration.

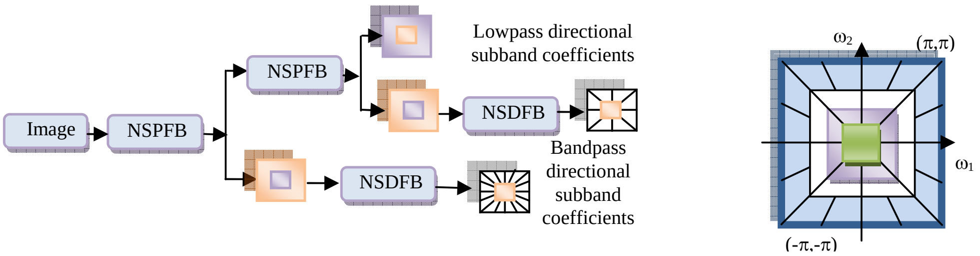
In this paper, robust feature-based registration for CT-MR images has been presented based on NSCT, MI and PSO. The medical images were first decomposed using the NSCT, then edge and CP was extracted from bandpass directional subband of NSCT coefficients and some adjacent rules. After edge and CP extraction, mutual information was adopted for the registration of feature points and transformation parameters are calculated by using particle swarm optimization (PSO). There are three main steps carried out for proposed feature-based image registration, edge detection using NSCT transform, optimization the MI based on particle swarm optimization and transformation parameters estimation. The experimental results demonstrate the robustness, efficiency and accuracy of the algorithm.

Nemir Al-Azzawi is with the School of Electrical and Electronic Engineering, USM, Malaysia, phone: +(60)173940264; (e-mail: nemir_azzawi@ ieee.org).

Harsa Amylia Mat Sakim is with the School of Electrical and Electronic Engineering, USM, Malaysia, phone: +6(03) 2681 0581 (e-mail: amylia@eng.usm.my).

Wan Ahmed K. Wan Abdullah is with the Radiology, School of Medical Sciences, USM, Malaysia,

Yasmin Mohd Yacob is with the School of Electrical and Electronic Engineering, USM, Malaysia.



(a) (b)

Fig. 1 (a) Nonsubsampled contourlet transform NSCT. (b) Resulting frequency division.

II. Nonsubsampled Contourlet Transform

Do and Vetterli developed a true 2-D image representation method, namely, the contourlet transform [11], which is achieved by combining the LP [12] and the directional filter bank (DFB) [13]. Compared with the traditional wavelet, contourlet transform can represent edges and other singularities along curves much more efficiently due to ability to multi-direction and anisotropy. However, the contourlet transform lacks the shift-invariance, which is desirable in many image applications. In 2006, Cunha et al. [8] proposed the NSCT which is a fully shift-invariant version of the contourlet, and multidirectional expansion that has a fast implementation. The NSCT eliminates the downsamplers and the upsamplers during the decomposition and the reconstruction of the image; instead, it is built ahead the nonsubsampled pyramids filter banks (NSPFBs) and the nonsubsampled directional filter banks (NSDFBs). The NSPFB, employed by the NSCT, is a two-channel nonsubsampled filter bank (NFB). The NSCT is obtained by carefully combining the NSPFB and the NSDFB [8], as shown in Fig. 1.

III. The Proposed Registration Algorithm

Given two images, I_R (defined as a reference image) and I_U (defined as a unaligned image) to match the reference image, the goal of image registration is to fix the unaligned image into the coordinate system of the reference image and to make corresponding coordinate points in the two images fit the same geographical location. In this section, we present the registration algorithm. There are three main steps carried out for registration.

A. Edge Detection using NSCT transform

In order to extract two sets of feature points, $CP1_i$ (i=1,2,…$N1$) and $CP2_i$ (i=1,2,…$N2$) from the reference and the unaligned images respectively, a NSCT-based feature points extraction method is employed. The method can be summarized by the following steps:

Step 1 : Compute the NSCT coefficients of both reference and unaligned images for *J*-levels.

Step 2 : Using only bandpass directional subband coefficients, compute the maximum magnitude of all directional subbands at a specific level *J*, where it's contained all high frequency that can be extracted edges. This call "NSCT-maxima image. At this step we get NSCT- maxima reference image and NSCT- maxima unaligned image.

Step 3 : Control points CP is found by applying a threshold procedure Th_j to both NSCT-maxima reference and unaligned image respectively. Using [10, 14] following rule:

$$Th_j = c(s_j + m_j) \tag{1}$$

where, c is a constant defined by the user and s_j and m_j are the standard deviation and mean of the NSCT maxima image. A low standard deviation indicates to be very close to the same value (the mean), while high standard deviation indicates that the data are spread out over a large range of values.

Step 4 : The locations of the obtained threshold NSCT-maxima $CP1_i$ (i=1,2,…$N1$) and $CP2_i$ (i=1,2,…$N2$) are taken as the extracted feature points. where $CP1_i$, $CP2_i$ are the coordinates and $N1$,$N2$ are the number of feature points. An example of the feature points detected is shown in Fig. 3.

B. Optimizing the MI based on PSO

After the feature points of two images have been extracted, mutual information is employed as a similarity measure to be optimized. Since MI made its entrance into the field of medical image registration, it has been adopted by a large number of researchers [15-17]. The mutual information of two random variables A and B is defined by following:

$$I(A,B) = \sum_{a,b} P_{AB}(a,b) \log \frac{P_{AB}(a,b)}{P_A(a).P_B(b)} \tag{2}$$

The interpretation of this form is that it measures the distance between the joint distribution of the images grey values $p(a,b)$ and the joint distribution in case of independence of the images, $p(a)$ $p(b)$. It is a measure of dependence between two images. The statistic relativity between the pixel information can be set as follows:

$$I(A,B) = H(A) + H(B) - H(A,B) \tag{3}$$

where $H(A)$ is the Shannon entropy of image A and $H(A,B)$ is joint entropy [15]. The implementation of MI are discussed particularly in [10]. Let $X_i=\{X_i, i=1,2,\ldots,N_1\}$ be points of NSCT-maxima reference image and $Y_j=\{Y_j, j=1,2,\ldots,N_2\}$ be points of NSCT-maxima unaligned image. The mutual information between the point-sets is a function of the joint probability as follows:

$$MI(X,Y)=\sum_{i=1}^{N1}\sum_{j=1}^{N2} P_{ij}\log\frac{P_{ij}}{\sum_{k=1}^{N1}P_{kj}\sum_{l=1}^{N2}P_{il}} \quad (4)$$

where the joint probability P_{ij} is the association probability between indices.

The origin of the Particle Swarm Optimization (PSO) [18], was based on the social behavior of the animals, such as bird flocking. In PSO, each solution of the problem, called particle, flies in the D-dimensional space with the velocity dynamically adjusted according to the individual information and population information. It has been proposed as global optimization technique [18-19], which is a stochastic, population-based evolutionary computer algorithm. PSO algorithm is implemented to optimize the objective function of $MI(X,Y)$. The Basic PSO algorithm consists of the velocity:

$$v_i(k+1)=v_i(k)+g_{1i}(p_i-x_i(k))+g_{2i}(p_g-x_i(k)) \quad (5)$$

and position:

$$x_i(k+1)=x_i(k)+v_i(k+1) \quad (6)$$

where, i is particle index, k is discrete time index, v_i is velocity of i^{th} particle, x_i is position of ith particle, p_i is best position found by i^{th} particle (personal best), p_g is best position found by swarm (global best, best of personal bests) and g_{1i}, g_{2i} are random numbers on the interval [0,1] applied to i^{th} particle. The PSO can be easily extended [6, 20]. By assuming a set of m particles in D-dimensional searching space, in which the first particle stands for a D-dimensional vector $\vec{x}_i=(x_{i1},x_{i2},\ldots,x_{iD})$, $i=1,\ldots m$ it is the position of $\vec{x}_i$. In other terms, every position is a prospective resolution. The corresponding value is getting if $\vec{x}_i$ is set to the target function. Set the present optimal position of the first particle is $\vec{p}_i=(p_{i1},p_{i2},\ldots,p_{iD})$, $i=1,\ldots m$. The present optimal position of the swarm is $\vec{p}_g=(p_{g1},p_{g2},\ldots,p_{gD})$, $i=1,\ldots m$. Operating the particles with the formulas:

$$v_i(k+1)=\omega(k)\,v_i(k)+a_1[g_{1i}(p_i-x_i(k))]+ a_2[g_{2i}(p_g-x_i(k))],\quad i=1,\ldots,m \quad (7)$$

where, ω is inertia function and $(a_{1\,or\,2})$ is nonnegative acceleration constants. $v_i\in[-v_{max},v_{max}]$, v_{max} is a constant value and it is set by the user. The ending condition of the iteration is essentially decided by the largest iteration or the threshold of the optimal position of the particles. We take the MI, which is depending on the parameters as the value of the target function.

C. Transformation Parameters Estimation

Image geometrical deformation has many different ways of description [5, 21-22]. Combination of rotation, scaling and translation is the most common one and it has five parameters: $\{t_x,t_y\}$ translation, rotation $\{\theta\}$, and scale $\{s_x,s_y\}$. This type of transformations is considered. Given the two sets of corresponding feature point coordinates optimum CP, the estimation of the transformation parameters, required to transform the unaligned image into its original size, direction, and position.

IV. Numerical Experiments

To test our algorithm, thirty groups of human brain images were selected. By using MRI image as reference and CT image as unaligned. The images have the size of 256×256 pixel, with 256-level grayscale. The simulation results have been obtained using the MATLAB software package. The experiment was implemented according to the following settings: The NSCT decomposition of images, performed using the NSCT toolbox, was carried out with level= [0,1,3] directional filter bank, decomposition levels at each pyramidal level (from coarse to fine scale) and c=1.8. Fig. 2, it shows the target registration error (TRE) in (mm) in all images tests. It can be easily shown in Fig. 3, that the registration results based on NSCT is accurate. So the method proposed in the paper is applicable in the medical image registration system.

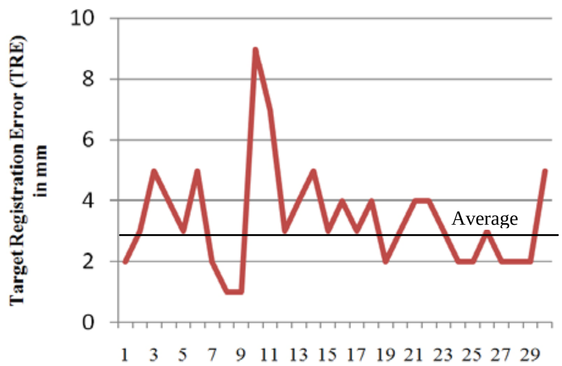


Fig. 2 The target registration error (TRE) in (mm) in all images tests.

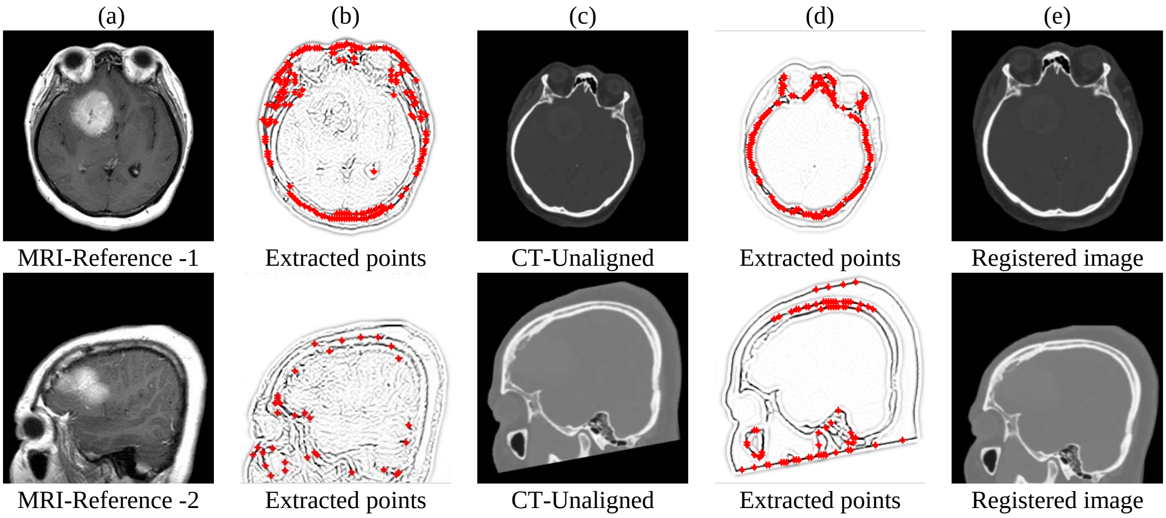


Fig. 3 (a) Input Reference image, (b) NSCT-maxima reference image marked by the extracted feature points (c) Unaligned image (d) NSCT-maxima unaligned image marked by the extracted feature points (d) Image registered.

V. Conclusions

In this paper, we have introduced an efficient feature-based registration for CT-MR images, which is employing NSCT transform. As a result, the proposed method gives promising results. The speed of searching for the optimum value is also improved after using PSO. According to the experiments, we can conclude that the method proposed is maintaining good performance; however, experiments show that our method works well for multimodal medical image registration. We have only considered the two-dimensional registration. Our further work is to apply the method to three-dimensional registration.

Acknowledgment

Part of this work is supported by USM research university grant no. 814012.

References

[1] J. V. Hajnal, et al., "Medical image registration." Boca Raton: CRC Press, 2001.
[2] A. Goshtasby, "2-D and 3-D image registration for medical, remote sensing, and industrial applications." Hoboken, NJ: J. Wiley & Sons, 2005.
[3] S. Rusinkiewicz and M. Levoy, "Efficient variants of the ICP algorithm," in Proceedings Third International Conference on 3-D Digital Imaging and Modeling, Quebec City, 2001, pp. 145-152.
[4] E. Meijering, et al., "Tracking in molecular bioimaging," IEEE Signal Processing Magazine, 23(3), pp. 46-53, 2006.
[5] B. Zitova and J. Flusser, "Image registration methods: A survey," Image and Vision Computing, 21(11), pp. 977-1000, 2003.
[6] W. Anna, et al., "A novel medical image registration algorithm based on PSO and wavelet transformation combined with 2v-SVM," in Second International Conference on Innovative Computing, Information and Control, ICICIC '07, Kumamoto, Japan 2007, pp. 584-588.
[7] A. Wang, et al., "A novel medical image registration algorithm based on PSO and wavelet transformation combined with 2v-SVM," in 2nd International Conference on Innovative Computing, Information and Control, ICICIC 2007, Kumamoto, Japan, 2008, pp. 584-588.
[8] A. L. d. Cunha, et al., "The nonsubsampled contourlet transform: theory, design, and applications," IEEE Transactions on Image Processing, 15(10), pp. 3089-3101, 2006.
[9] J. P. Zhou, et al., "Nonsubsampled contourlet transform: construction and application in enhancement," in IEEE International Conference on Image Processing, ICIP2005, Genoa, Italy, 1, 2005, pp. 469-472.
[10] A. Rangarajan, et al., "Rigid point feature registration using mutual information," Medical Image Analysis, 3(4), pp. 425-440, 1999.
[11] M. N. Do and M. Vetterli, "“Contourlets,” in Beyond Wavelets," Academic Press, New York, 2003.
[12] P. Burt and E. Adelson, "The Laplacian pyramid as a compact image code," IEEE Transactions on Communication, 31(4), pp. 532-540, 1983.
[13] R. H. Bamberger and M. J. T. Smith, "A filter bank for the directional decomposition of images: Theory and design," IEEE Transactions on Signal Processing, 40(4), pp. 882-893, 1992.
[14] C. Serief, et al., "Robust feature points extraction for image registration based on the nonsubsampled contourlet transform," AEU - International Journal of Electronics and Communications, 63(2), pp. 148-152, 2009.
[15] J. P. W. Pluim, et al., "Mutual-information-based registration of medical images: a survey," IEEE Transactions on Medical Imaging, 22(8), pp. 986-1004, 2003.
[16] A. Gholipour, et al., "Brain functional localization: A survey of image registration techniques," IEEE Transactions on Medical Imaging, 26(4), pp. 427-451, 2007.
[17] F. Maes, et al., "Multimodality image registration by maximization of mutual information," IEEE Transactions on Medical Imaging, 16(2), pp. 187-198, 1997.
[18] J. Kennedy and R. C. Eberhart, "Particle swarm optimization," in Proceedings of IEEE International Conference on Neural Networks, Piscataway, NJ, 4, 1995, pp. 1942-1948.
[19] B. Birge, "PSOt - a particle swarm optimization toolbox for use with Matlab," in Proceedings of the 2003 IEEE Swarm Intelligence Symposium, 2003. SIS '03, Indianapolis (IN), USA, 2003, pp. 182-186.
[20] W. Benzheng, et al., "An improved PSO algorithm based multimodality medical image automatic registration," in Fourth International Conference on Natural Computation, ICNC '08, Jinan, 7, 2008, pp. 574-578.
[21] L. G. Brown, "A survey of image registration techniques," ACM Computing Surveys, 24(4), pp. 325-376, 1992.
[22] A. E. R. Arce-Santana and A. Alba, "Image registration using Markov random coefficient and geometric transformation fields " Pattern Recognition 42(8), pp. 1660-1671, 2009.