Rigid medical image registration using PCA neural network

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Abstract

Medical image registration plays an important role in clinical diagnosis and therapy planning. This paper proposes an automatic method to register computed tomography (CT) and magnetic resonance (MR) brain images by using first principal directions of feature images. In this method, principal component analysis (PCA) neural network is used to calculate the first principal directions from feature images, then the registration is accomplished by simply aligning feature images’ first principal directions and centroids. Simulations for MR–MR (MR and MR images) registration and CT–MR (CT and MR images) registration are carried out to illustrate the method.

Keywords: Image registration; Principal component analysis; Oja’s learning algorithm; Neural network

1. Introduction

It is common for patients to undergo multiple tomographic radiological imaging for the purpose of medical diagnosis. These multi-modality images provide complementary information. However, it is difficult for doctors to fuse these images exactly due to the variations in patient orientation. For this reason, there has been considerable interest in using image registration to transfer all the information into a common coordinate frame. The objective of this study is to find a transformation which best aligns the float image (unregistered image) with the reference image.

Many registration methods have been developed over decades [12]. In general, these methods are based either on original images or on feature images. Among these methods, commonly used registration techniques include Fourier transform [9], mutual information [7], and cross-correlation method [1]. Recently, the registration method using mutual information is very popular. This method can register multi-modality medical images accurately without preprocessing. However, the mutual information computation is complex and costs much time. So there has been considerable interest in finding new methods to rapidly register medical images.

The proposed method based on feature images accomplishes registration by simply aligning feature images’ first principal directions and centroids. The objective of this method is to find parameters (rotation angle, translations along the X- and Y-axis) for registration. This method consists of three steps:

(1) Extracting features: For computed tomography–magnetic resonance (CT–MR) registration, extracted contours are used as feature images. On the other hand, for MR–MR registration, threshold segmented images are used as feature images. The next two steps are based on feature images obtained in this step.

(2) Computing the rotation angle: The proposed method uses a principal component analysis (PCA) neural network to compute the first principal direction of the reference feature image and that of the float feature image, then the angle between the two directions is simply calculated, which is used as the rotation angle.

(3) Computing translations: Translations are calculated as subtracting float feature image’s centroid from reference feature image’s centroid.
In the procedure above, the crucial step is calculating the first principal direction by using PCA neural network [4,5,8,11,14]. Since a PCA neural network can compute the principal direction more easily, the computation is simplified. Moreover, the principal direction usually converges to a unit vector, which makes the computation of rotation angle simpler.

The content of this paper is organized as follows. Section 2 gives the procedure of the proposed method. Section 3 shows the experimental results of CT–MR registration and MR–MR registration. The main conclusions are summarized in Section 4.

2. Method

The proposed method consists of three steps: (1) extracting features; (2) computing the rotation angle; (3) computing translations. The 2-D images in Figs. 1 and 2 are used to illustrate the procedure.

2.1. Extracting features

In general, the implementation of medical image registration is either on original images or on feature images. The proposed registration method is implemented on feature images.

For MR–MR registration, threshold segmented images are used as feature images. The procedure of threshold segmentation consists of two steps: (1) setting a threshold θ to lie within [0, 255]; (2) comparing image’s intensity values with θ, where values larger than θ are set to be 1, and all the others are set to be 0. Fig. 1 shows threshold segmentation results. Fig. 1(a) and (c) are MR images of a patient taken at different times. Fig. 1(a) is used as the reference image, and Fig. 1(c) is the corresponding float image. Fig. 1(b) and (d) are feature images of Fig. 1(a) and (c) with threshold 40, respectively. In this paper, Fig. 1(b) is called reference feature image and Fig. 1(d) is called float feature image.

For CT–MR registration, contours are used as feature images. In this paper, contour tracking method is applied to extracting contour information. The detailed procedure of this method can be found in [13]. Fig. 2 shows contour extraction results with contour tracking method. Fig. 2(a) is a patient’s CT image, which is used as the reference image. The MR image in Fig. 2(c) is used as the float image. Fig. 2(b) and (d) are feature images of Fig. 2(a) and (c), respectively.

2.2. Computing the rotation angle

Computing the rotation angle is an important step for rigid medical image registration. In this section, we present...
the way of finding the rotation angle that relates to feature images obtained in the previous section.

If an image is rotated, it is clear that the rotation angle is equal to the rotation angle of its first principal direction. See the Appendix for the mathematical fundamentals. In the proposed method, the first principal direction of the reference feature image and that of the float feature image is computed by using a PCA neural network, then it is easy to get the rotation angle, which is the angle between the two first principal directions.

Registration methods using neural networks have been developed in recent years [2,3,6]. In the proposed method, Oja’s PCA neural network is used to compute the first principal direction. Oja’s network can compute the principal direction of a data set [4]. Suppose the input sequence \( \{x(k) = [x_1(k), x_2(k), \ldots, x_n(k)]^T | x(k) \in \mathbb{R}^n (k = 0, 1, 2, \ldots) \} \) is a zero mean stationary stochastic process and let \( C_k = x(k)x^T(k) \), then the Oja’s PCA learning algorithm can be described by the following stochastic difference equation:

\[
w(k + 1) = w(k) + \eta[C_kw(k) - w^T(k)C_kw(k)w(k)],
\]

(1)

where \( \eta \) is the learning rate and \( w(k) = [w_1(k), w_2(k), \ldots, w_n(k)]^T \). If the learning rate \( \eta \) satisfies some simple conditions, the \( w \) will converge to the first principal direction [14,15]. The single layer neural model shown in Fig. 3 is used to extract the first principal direction and (1) is its learning algorithm.

In our applications, the reference feature image and the float feature image are quantified into input sequences \( \{r(k)\} \) and \( \{f(k)\} \), respectively, where

\[
r(k) = \begin{pmatrix} x_1^r(k) \\ x_2^r(k) \end{pmatrix} \quad \text{and} \quad f(k) = \begin{pmatrix} x_1^f(k) \\ x_2^f(k) \end{pmatrix},
\]

for all \( k \geq 0 \). By using Oja’s algorithm (1), it is easy to obtain the reference feature image’s first principal direction \( W_R = [r_x, r_y]^T \) with \( \|W_R\| = 1 \) and the float feature image’s first principal direction \( W_F = [f_x, f_y]^T \) with \( \|W_F\| = 1 \). The angle between the two vectors is calculated as follows:

\[
A_{\theta_0} = |\arccos(W_R^T \cdot W_F)|,
\]

(2)

where \( A_{\theta_0} \) is the absolute value of rotation angle.

Since the rotation angle is usual within \([-30^\circ, 30^\circ]\), it is calculated according to

\[
\theta = \begin{cases} 
\text{sgn}(f_y/r_y) \cdot A_{\theta_0}, & \text{sgn}(r_y/r_x) \neq \text{sgn}(f_y/f_x), \\
\text{sgn}(r_y/r_x - f_y/f_x) \cdot A_{\theta_0}, & \text{sgn}(r_y/r_x) = \text{sgn}(f_y/f_x), 
\end{cases}
\]

(3)

where the function \( \text{sgn} \) is defined as follows:

\[
\text{sgn}(x) = \begin{cases} 
1, & x > 0, \\
0, & x = 0, \\
-1, & x < 0.
\end{cases}
\]

2.3. Computing translations

After deriving the rotation angle, now we present the way of computing translations for registration.

Consider a data set \( \{X_i|X_i = [x_i, y_i]^T, 1 \leq i \leq N\} \). With knowledge of physics, its centroid \( [X_c, Y_c] \) is computed by follows:

\[
X_c = \frac{1}{N} \sum_i x_i, \quad Y_c = \frac{1}{N} \sum_i y_i.
\]

(4)

From (4), float feature image’s centroid \( [X'_c, Y'_c] \) and reference feature image’s centroid \( [X''_c, Y''_c] \) are obtained. Translations are calculated as subtracting the float feature image’s centroid from the reference feature image’s centroid:

\[
del X = X'_c - X''_c, \quad del Y = Y'_c - Y''_c.
\]

(5)

where \( del X \) and \( del Y \) are translations along the \( X \)- and \( Y \)-axis, respectively.

3. Simulations

This section includes two examples to illustrate the proposed method.

3.1. MR–MR registration

Fig. 4 shows the result of MR–MR registration. Fig. 4(a) is used as the reference image, and Fig. 4(c) is the corresponding float image which is obtained by a sequential rotation and translation operation with the MRICro software (http://www.psychology.nottingham.ac.uk). Fig. 4(b) and (d) are feature images of Fig. 4(a) and (c), respectively. With PCA neural network, the first principal direction of Fig. 4(b) is \([0.037, 0.999]^T\) and that of Fig. 4(d) is \([-0.376, 0.926]^T\). Then by (2) and (3), the rotation angle is \(-20.11^\circ\). By subtracting the centroid of Fig. 4(d) from the centroid of Fig. 4(b), the translations along the \( X \)- and \( Y \)-axis are \(-1.1 \) and \( 8.1 \) pixels, respectively.

To facilitate the examination of the proposed method, the registered image’s contour and the reference image’s contour are compared in Fig. 4(f). Clearly, the two
Fig. 4. MR–MR registration: (a) reference image and (b) its feature image with threshold 31. (c) float image and (d) its feature image with threshold 31. (e) comparison of contours before registration versus (f) after registration.

Fig. 5. CT–MR registration: (a) patient’s head CT image and (b) its contour, centroid, principal directions. (c) patient’s head MR image and (d) its contour, centroid, principal directions. (e) comparison of contours before registration versus (f) after registration.
contours almost overlap, which illustrates the proposed method is promising.

3.2. CT–MR Registration

Images used in this subsection are provided in the framework of “The Retrospective Registration Evaluation Project” (http://www.vuse.vanderbilt.edu/image/registration/) held by J. Michael Fitzpatrick from Vanderbilt University, Nashville, TN, USA. Fig. 5 shows the result of CT–MR registration. Fig. 5(a) is the reference image and 5(c) is the corresponding float image. Fig. 5(b) and (d) are feature images of Fig. 5(a) and (c), respectively. The reference image’s contour and registered image’s contour are compared in Fig. 5(f). Clearly, the two contours almost overlap, which illustrates the proposed method is promising for CT–MR image registration.

4. Conclusions

This paper proposes an automatic method for CT–MR registration and MR–MR registration. The proposed method based on feature images accomplishes registration by simply aligning the first principal directions and centroids of feature images. Since a PCA neural network is used to compute the first principal directions of feature images, the registration is simple and efficient.

Appendix

The rotation angle of an image is equal to the rotation angle of its first principal direction. The mathematical fundamentals are given in this Appendix.

First, we give a brief review of the traditional PCA [10]. Let vector \( X_i = [x_i, y_i]^T \) denote points of an image, and let \( N \) denote the number of these points. Clearly, its first principal direction \( W \) is defined as follows:

\[
W = \arg \max_{\tilde{W}} \langle \tilde{V}^T S \tilde{V} \rangle,
\]

where \( S \) is the correlation matrix and is given by

\[
S = \frac{1}{N} \sum_{i=1}^{N} (X_i - \mu)(X_i - \mu)^T, \quad \mu = \frac{1}{N} \sum_{i=1}^{N} X_i.
\]

Furthermore, the principal direction \( W \) is the eigenvector associated with the largest eigenvalue of the covariance matrix \( S \).

Suppose the image is rotated by angle \( \theta \). Let vector \( \tilde{X}_i = [\tilde{x}_i, \tilde{y}_i]^T \) denote points of the rotated image, and \( \tilde{X}_i \) is represented as follows:

\[
\tilde{X}_i = R \cdot X_i,
\]

where \( R \) is the rotation matrix and is given by

\[
R = \begin{bmatrix}
\cos(\theta) & -\sin(\theta) \\
\sin(\theta) & \cos(\theta)
\end{bmatrix}.
\]

Then, the first principal direction \( \tilde{W} \) of the rotated image is computed as follows:

\[
\tilde{W} = \arg \max_{\tilde{V}} \langle \tilde{V}^T \tilde{S} \tilde{V} \rangle,
\]

where

\[
\tilde{S} = \frac{1}{N} \sum_{i=1}^{N} (\tilde{X}_i - \tilde{\mu})(\tilde{X}_i - \tilde{\mu})^T, \quad \tilde{\mu} = \frac{1}{N} \sum_{i=1}^{N} \tilde{X}_i.
\]

By (7), it follows that

\[
\tilde{W} = \arg \max_{\tilde{V}} \langle (R^T \tilde{V})^T S (R^T \tilde{V}) \rangle.
\]

From (8) and (9), it is easy to get that

\[
\tilde{W} = RW.
\]

Eqs. (7) and (10) imply that the rotated image and its first principal direction have undergone the same rotation transformation.

References


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