Automated Registration of Multimodality Images by Maximization of a Region Similarity Measure

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Abstract

This paper presents a robust algorithm for automated registration of images related by rigid-body transformations. This algorithm uses a new region-based similarity metric, which enables accurate registration of images of large contrast differences. Region segmentation required by the metric is accomplished using a multiscale segmentation algorithm, and minimization of this metric is done using the Powell direction set method. Experimental results are presented to demonstrate that the algorithm is effective for aligning images from single or multiple imaging modalities without the use of any fiducial markers.

1 Introduction

Image registration is a fundamental problem in image processing. Its primary task is to match two or more images acquired at different times and/or from different imaging modalities. The need for image registration arises in various practical problems. In biomedical imaging, for example, it is often necessary to align images obtained from computed tomography (CT), magnetic resonance imaging (MRI) and positron emission tomography (PET) so that complementary information from these modalities can be utilized simultaneously to improve diagnosis and treatments. Even with a single imaging modality, image registration is often useful for correcting image displacements and rotations due to object motion in serially acquired images.

Over the years, a broad range of techniques have been developed to deal with the image registration problem for various types of data. For a comprehensive review and a taxonomy of the techniques developed before 1993, one is referred to [1, 2]. A recent comparative study of some of these methods can be found in [3]. Generally speaking, rigid-body registration of images with similar contrast is a solved problem. Many methods, including the Fourier transform-based method [4] or the voxel-similarity-based method [5] can align images of this type with sub-pixel accuracy. However, for images with significant contrast differences, such as those from different imaging modalities, the problem has been challenging because of the lack of an effective matching criterion. To address this problem, new methods for automated registration of multimodality images continue to appear [6]. This paper describes another such method. A key contribution here is a new region similarity metric which can effectively handle images with large contrast differences. Details of this technique are provided in the subsequent section. Sample experimental results are shown in Section 3, which is followed by the concluding remarks.

2 The Proposed Method

Given a pair of images to register, we may designate one of them, say $I_1(x,y)$, as the reference image and the other one, $I_2(x,y)$, as the floating image. The goal is to find a coordinate transformation $\mathbf{T}$ such that $\mathbf{T}\{I_2\}$ is maximally "similar" to I_1. In this paper, we consider only the case that $\mathbf{T}$ is a rigid-body transformation so that $\mathbf{T}$ can be decomposed as a shift $\mathbf{T}_s$ and a rotation $\mathbf{T}_r$. In the 2D case, $\mathbf{T}_s$ is a function of two shift parameters Δx and Δy, and $\mathbf{T}_r$ is a function of a single rotation parameter $\Delta\theta$. In the following discussion, we will discuss how to find the registration parameters using a new region-based similarity measure and the Powell direction set optimization method.

2.1 Region Similarity Measure

The similarity measure is one of the most important elements in a registration technique. It determines what features are being matched in the registration process. A number of similarity measures has been used in various registration techniques. Some popular ones are cross-correlation, sum of squared differences, voxel similarity [5], and mutual information [6]. In this paper we propose a new region-based similarity measure. Specifically, we first decompose I_1 into a set of $N_{r,1}$ "homogeneous" regions denoted as $\{\mathcal{R}_1(n); n = 1, \cdots, N_{r,1}\}$, and I_2 into a set of $N_{r,2}$ homogeneous regions denoted as $\{\mathcal{R}_2(n); n = 1, \cdots, N_{r,2}\}$. Here a homogeneous region is defined as a set of connected pixels over which the image intensity variation is below a certain threshold. An algorithm for extracting such regions will be discussed in the ensuing subsection. Note that with the proposed registration algorithm it is not necessary to assume that $N_{r,1} = N_{r,2}$ or $\mathcal{R}_1(n) = \mathcal{R}_2(n)$. This significantly relaxes the burden on region segmentation since each image can be processed independently.

With $\mathcal{R}_1(n)$ and $\mathcal{R}_2(n)$ defined, we superimpose the region definitions of I_1 onto I_2 and vice versa. Although $\mathcal{R}_1(n)$ and $\mathcal{R}_2(n)$ are homogeneous with respect to I_1 and I_2, respectively, the level of homogeneity of I_2 over $\mathcal{R}_1(n)$ and I_1 over $\mathcal{R}_2(n)$ clearly depends on the relative position of the two images. Let $\sigma^2_{1,2}(n)$ denote the regional image intensity variance of I_2 over $\mathcal{R}_1(n)$, and $\sigma^2_{2,1}(n)$ denote the regional image intensity variance of I_1 over $\mathcal{R}_2(n)$. Then we have

$$\begin{aligned}\sigma^2_{1,2}(n) &= \frac{1}{N_{p,1}(n)} \sum_{(x,y)\in\mathcal{R}_1(n)} [I_2(x,y) - \bar{I}_{1,2}(n)]^2, \\ \sigma^2_{2,1}(n) &= \frac{1}{N_{p,2}(n)} \sum_{(x,y)\in\mathcal{R}_2(n)} [I_1(x,y) - \bar{I}_{2,1}(n)]^2,\end{aligned}$$

where $N_{p,1}(n)$ and $N_{p,2}(n)$ are the numbers of pixels in $\mathcal{R}_1(n)$ and $\mathcal{R}_2(n)$, respectively, and $\bar{I}_{1,2}(n)$ and $\bar{I}_{2,1}(n)$ are the regional average image intensities. One can argue that to a first approximation, $\sigma^2_{1,2}(n)$ and $\sigma^2_{2,1}(n)$ measure the registration error between I_1 and I_2 using $\mathcal{R}_1(n)$ or $\mathcal{R}_2(n)$ as landmark features. Taking into account all the regions identified in I_1 and I_2, we define the registration error E_r between I_1 and I_2 as the sum of $\sigma^2_{1,2}(n)$ and $\sigma^2_{2,1}(n)$ weighted by the sizes of the regions:

$$E_r = \sqrt{\sum_{n=1}^{N_{r,1}} N_{p,1}(n)\sigma^2_{1,2}(n) + \sum_{n=1}^{N_{r,2}} N_{p,2}(n)\sigma^2_{2,1}(n)}.$$

Clearly, minimizing E_r effectively forces the homogeneous regions of I_1 to correspond to those of I_2 and vice versa. As a result, it becomes easier to predict I_1 from I_2 or I_2 from I_1. In other words, minimizing E_r enhances the cross-correlation or mutual information between I_1 and I_2. Therefore, in this sense, E_r may be viewed as a region-based mutual information criterion in contrast to the pixel-based mutual information criterion used in [6]. The effectiveness of this metric will be demonstrated in Section 3.

2.2 Region Segmentation

Region segmentation is a classical image processing problem, for which many algorithms have been proposed [7, 8]. Since the proposed similarity metric does not require exact matching of $\mathcal{R}_1(n)$ and $\mathcal{R}_2(n)$ to individual anatomical structures, region segmentation here is not as challenging as in other applications involving structural identification. We choose the region segmentation algorithm proposed in [7] to extract $\mathcal{R}_1(n)$ and $\mathcal{R}_2(n)$ from I_1 and I_2, respectively, because of its robustness.

A distinct feature of the algorithm as compared with other multiscale segmentation algorithms, such as the one in [8], is the use of a nonlinear transform [7]. This transform maps an image, $I(x,y)$, into a family of force fields, $\mathbf{F}(x,y;\sigma_i,\sigma_s)$, defined as

$$\mathbf{F}(x,y;\sigma_i,\sigma_s) = \sum_{u\neq x}\sum_{v\neq y} d(\Delta I,\sigma_i)d(\vec{r},\sigma_s)\frac{\vec{r}}{\|\vec{r}\|},$$

where σ_i and σ_s are parameters specifying the intensity and spatial scales,

$$\begin{aligned}\Delta I &= I(x,y) - I(u,v), \\ \vec{r} &= (u-x)\vec{i} + (v-y)\vec{j}, \quad \text{and} \\ d(x,\sigma) &= \begin{cases} 1, & |x| \leq \sigma, \\ 0, & \text{otherwise.}\end{cases}\end{aligned}$$

The transform computes at each pixel a vector sum of pairwise affinities between the pixel and all other pixels in the image. The resulting vector represents the direction and magnitude of attraction experienced by the pixel from the rest of the image. With this force field, pixels are grouped together into regions whose boundaries correspond to diverging force vectors in $\mathbf{F}$ and whose skeleton correspond to converging force vectors in $\mathbf{F}$. Implementation details of this algorithm can be found in [7].

2.3 Minimization of E_r

Minimization of E_r to find the registration parameter vector $(\Delta x, \Delta y, \Delta\theta)$ is an important step of the proposed registration algorithm. For notational simplicity, let $\vec{\xi} = (\Delta x, \Delta y, \Delta\theta)$. We can then explicitly write E_r as a function of $\vec{\xi}$ with the understanding that

$$E_r(\vec{\xi}) = E_r[I_1, \mathbf{T}(\vec{\xi})\{I_2\}].$$

The optimal registration parameter vector $\vec{\xi}^*$ is given by

$$\vec{\xi}^* = \arg\min_{\vec{\xi}} E_r(\vec{\xi}).$$

Because $E_r(\vec{\xi})$ is a nonlinear function of $\vec{\xi}$, finding $\vec{\xi}^*$ requires the solution of a multivariate nonlinear problem. As in most optimization algorithms, we start with an initial estimate $\vec{\xi}_0$ and then improve it iteratively.

To find a good initial estimate, we take advantage of the Fourier transform property of a rotated and translated signal. Specifically, we first convert both I_1 and I_2 to binary images denoted here as $\bar{I}_1$ and $\bar{I}_2$. This step is aimed at eliminating the contrast difference between the two images. As a result, $\bar{I}_2$ is roughly a translated and rotated version of $\bar{I}_1$. We next evaluate the Fourier transform of $\bar{I}_1$ and $\bar{I}_2$ along a circle of radius k_0, yielding

$$\begin{aligned} S_1(\theta) &= \sum_x \sum_y \bar{I}_1(x,y) e^{-i2\pi k_0 (x\cos\theta + y \sin\theta)}, \\ S_2(\theta) &= \sum_x \sum_y \bar{I}_2(x,y) e^{-i2\pi k_0 (x\cos\theta + y \sin\theta)}. \end{aligned}$$

It is easy to show that

$$S_2(\theta) \approx S_1(\theta + \Delta\theta_0) e^{-i2\pi k_0 (\Delta x_0 \cos\theta + \Delta y_0 \sin\theta)}.$$

Based on the above relationship, $\Delta\theta_0$ can be extracted from the magnitude of S_1 and S_2, whereas Δx_0 and Δy_0 can be obtained from the phase term. A more detailed discussion on the selection of k_0 and estimation of Δx_0, Δy_0 and $\Delta\theta_0$ from S_1 and S_2 can be found in [9].

Starting from $\vec{\xi}_0 = (\Delta x_0, \Delta y_0, \Delta\theta_0)$, we search for the global minimum iteratively as

$$\vec{\xi}_{n+1} = \vec{\xi}_n + \Delta\vec{\xi}_n,$$

where $\Delta\vec{\xi}_n$ specifies the search stepsize and direction in the nth iteration. A number of methods can be used to determine $\Delta\vec{\xi}_n$. For example, with the gradient descent method,

$$\Delta\vec{\xi}_n = -\lambda \nabla E_r(\vec{\xi}_{n-1}),$$

where λ controls the stepsize, which can be chosen using a variety of schemes [10]. We have found that E_r is often a smooth function, and the gradient search method works reasonably well. However, as in other applications, gradient-based optimization methods have a tendency to converge to a local minimum, which may give unacceptable registration results.

To avoid this problem we use the Powell direction set method. In its basic form [10], the Powell method selects a set of unit vectors $\vec{e}_x$, $\vec{e}_y$, and $\vec{e}_\theta$, pointing along the x, y, and θ directions, respectively, in the parameter space. It then uses a line search method to move along the first direction to its minimum, then from there along the second direction to its minimum, and so on, cycling through all three directions as many times as necessary until E_r stops decreasing. Advanced versions of the Powell method use different schemes to update the search directions, thereby speeding up the convergence of the algorithm. Detailed discussion of these issues can be found at [10].

3 Results and Discussion

The performance of the proposed registration criterion has been evaluated using MR images of different contrast One example is shown in Fig. 1(a) and (b), in which the images were obtained using a T_1-weighted spin-echo sequence with $T_R = 200$ ms and 1500 ms, respectively. In this study, image (b) is shifted 23 pixels to the left and rotated 23° degrees relative to image (a). The similarity measure $(1/E_a)$ calculated from the two images with different values of Δx and $\Delta\theta$ is presented in Fig. 1(c). As can be seen, the peak location accurately predicts the relative position of the two images. Note also that the similarity surface is smooth. For this example, both the gradient search method and the Powell direction set method converged to the global minimum correctly. With the current version of the computer code which is not yet optimized for computational efficiency, it took less than 15 seconds for the algorithm to converge to the correct results in a SGI (Silicon Graphics, Inc.) Indigo workstation.

The proposed algorithm has also been tested with multimodality images. An example of MRI to CT registration is presented in Fig. 2. As can be seen, the two images used in this example have totally different contrast with the CT image being rotated 14.5°. The proposed algorithm was able to accurately determine the rotation angle, as indicated by the similarity measure plot in (c). Note that in this example, the original pixel size of the MR image was different from that of the CT image, and it was necessary to scale them before the registration algorithm was applied. It is possible to introduce a scaling parameter to the proposed algorithm so that scaling can be done automatically. This capability remains to be developed for the proposed algorithm.

4 Conclusion

A new algorithm for automated registration of images related by rigid-body transformations has been described in this paper. This algorithm is based on a new region similarity metric which enables accurate alignment of images with large contrast differences. The algorithm should prove useful for a variety of problems including bulk motion correction in functional brain mapping and registration of both intra- and inter-modality images.

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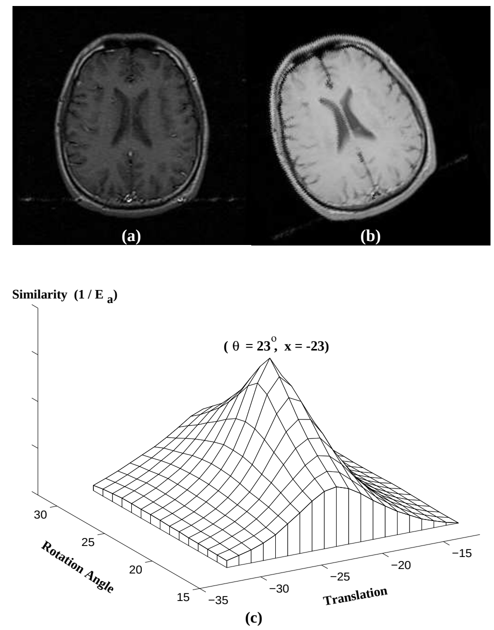

Figure 1: Brain images to be registered and the corresponding similarity measure for different values of Δx and $\Delta\theta$.

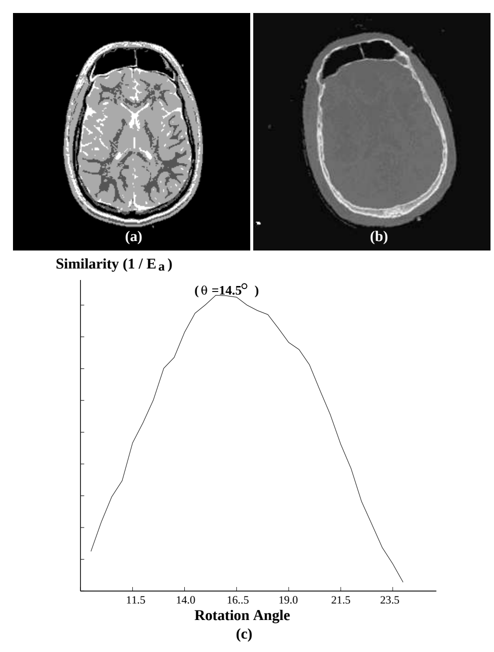

Figure 2: Registration of the MR image in (a) to the CT image in (b). The similarity measure for different values of $\Delta\theta$ is plotted in (c).