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Learning-based Deformation Estimation for Fast Non-rigid Registration

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Abstract

This paper presents a learning-based deformation estimation method for fast non-rigid registration. *First*, a PCA-based statistical deformation model is constructed using the deformation fields obtained by conventional registration algorithms between a template image and training subject images. *Then*, the constructed statistical model is used to generate a large number of sample deformation fields by resampling in the PCA space. In the meanwhile, by warping the template using these sample deformation fields, the respective sample images in the PCA space can be also generated. *Finally*, after learning the correlation between the features of the sample images and their deformation coefficients, given a new test image, we can immediately estimate its relative deformations to the template based on its image information. Using this estimated deformation, we can warp the template to generate an intermediate template close to the test image. Since the intermediate template is more similar to the test image compared to the original template, the deformable registration via the intermediate template becomes much easier and faster. Experimental results show that the proposed learning-based registration method can fast register MR brain image with robust performance.

1. Introduction

Non-rigid registration is an important technique for aligning images of different objects, or images of same subject acquired at different times. It has been extensively used in medical applications for facilitating the identification of brain abnormality by comparing between normal and abnormal groups, and for constructing the atlas to reflect the structural and functional variation of individual brains within a population.

Most deformable registration methods [1–4] aim to find shape deformations between two images by maximizing image similarity. However, for brain image registration, due to the complex of brain structures as well as the large variation of brain structures across different individuals, local minimum is a critical problem in brain image registration. To overcome this, various registration techniques have been proposed to incorporate statistical information to guide image registration, e.g., constraining the shape deformations estimated during the registration procedure [5–6]. Also, the learned brain deformation information can be used to generate the intermediate template for facilitating the image registration [7], since the generated intermediate template can be more similar to the test image, compared to the

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original template. However, these approaches for enhancing registration performance have limitation in their execution time due to high complexity of additional information used.

We here propose a learning-based deformation estimation method to fast generate an intermediate image, thus significantly reducing the computation time of brain registration. Actually, the learning-based methods have been widely used in the medical image analysis field for shape-based classification [8–9], shape estimation [10], and shape detection [11–12], as well as for learning the best features to reduce ambiguity in image registration [13].

In this paper, we propose to learn the correlations between the sample images and their respective deformation coefficients to the template. Thus, during the applications, based on the learned correlations and the given test image, we can immediately estimate the shape deformation coefficients for the test image. To do this, we will *first* construct a statistical deformation model from a set of training deformation fields using a PCA technique. *Then*, we will use this statistical deformation model to generate a number of new shape deformations in the PCA space, and to warp the template to various locations using these generated shape deformations. Given pairs of generated shape deformations and their respective warped template images, we use a regression model to learn the correlation between the shape deformations and the respective warped images. Since each shape deformation can be efficiently represented by PCA using a small number of coefficients, the dimensionality of deformation coefficients can be significantly reduced, thus facilitating the learning of the expected correlations by the regression model.

The experimental results show that this learned-based deformation estimation strategy can make the deformable registration completed five times fast than HAMMER algorithm, using the software available in the developer's website. At same time, the registration performance is close to the HAMMER algorithm [1].

2. Methods

In the following, we *first* construct a PCA-based statistical deformation model using the sample shape deformations obtained between training brain images and a selected template. *Then*, we generate a large number of sample shape deformations and their respective warped template images by using a constructed statistical deformation model. Sample shape deformations can be represented by coefficients in PCA space, and the warped template images can be compactly represented by signature maps as detailed in this section, thus we can use regression models to learn the correlation between deformation coefficients and image information.

In the applications, given a test image, we can use the learned correlation to immediately estimate a reasonable set of shape deformation coefficients to fast warp the template very close to the test image. The warped template is called as an intermediate template in this paper. It can be used as a bridge to connect the template with the test image (Fig. 1). Furthermore, by registering the intermediate template with the test image using a conventional registration algorithm, we can eventually create a path to register template with the test image.

2.1. Generation of pairs of sample deformations and sample images

The statistical deformation model is constructed by the shape deformations estimated between a template and a set of training images using HAMMER [1]. Principal component analysis (PCA) is used to construct the statistical deformation model [15]. After obtaining this model, a new shape deformation can be represented by a mean deformation $\bar{x}$,

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eigenvector matrix $\Phi = (\Phi_1, \Phi_2, \ldots, \Phi_n)$, and coefficient vector $b = (b_1\ b_2 \ldots b_n)^T$, as defined below:

$$x \approx \bar{x} + \Phi b \tag{1}$$

Since b represents the amount of variation in the eigenvector directions, we can generate various sample shape deformations by varying b within the statistically valid range, i.e., $|b_i| \le \pm 3\sqrt{\lambda_i}$. Moreover, by combining the eigenvectors and their respective coefficients, more shape deformations can be synthesized (Fig. 1). Generally, using more samples can potentially achieve the better correlation learned between the deformation coefficients and the warped template images. The synthesized shape deformation x_{samp} by combining the i-th and the j-th eigenvectors can be represented as follows:

$$\begin{aligned} &x_{samp} = \bar{x} + (b_i \cdot \mathbf{\Phi}_i + b_j \cdot \mathbf{\Phi}_j), \\ &i = 1, \ldots, n-1, \ \ j = 1, \ldots, n-1, \end{aligned} \tag{2}$$

where b_i, b_j are the two coefficients.

By using the synthesized deformation fields to warp the template image, we can obtain the respective warped template images as training samples. Examples of the sample images generated by the i-th and the j-th eigenvectors ($i > j$) and their combinations are shown in Fig. 2. Since the eigenvectors are sorted by the eigenvalues in descending order, the eigenvector with higher order controls more global shape variability of the sample images.

The correlation between the sample images and the deformation coefficients can be established with regression models as described below. The number of deformation coefficients is the same as the number of non-zero eigenvalues used in the statistical deformation model. Since the dimensionality of each sample image can be high, we need to down-sample these images to be low-dimensional for effective learning.

For effectively representing each down-sampled warped template image, we create its signature map. In particular, the intensity difference map between each down-sampled *warped* template image and the down-sampled *original* template image is used a signature map. Therefore, each signature map includes only the image information different from the original template. Also, for effective learning, each signature map will be also normalized.

2.2. Learning correlations between sample images and respective deformations

Although the dimensionality of signature map has been deducted using image down-sampling, its size is still much larger than that of deformation coefficients. We accordingly use PCA to further reduce the dimensionality of each signature map. PCA is trained based on all signature maps.

To learn the correlation between the dimension-deducted signature map and the respective deformation coefficients, we employ a number of support vector regression (SVR) models [14]. The number of SVR models is equal to the number of deformation coefficients used. That is, one SVR model is designed to capture the correlation of each deformation coefficient with all signature features. Each SVR model is trained by all training samples.

Selection of kernel function as well as kernel size is important for building good regression models. We use a radial basis function (RBF) as the kernel function for nonlinear regression. For selecting a suitable kernel size for RBF, we evaluate the distribution of training samples

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in the space of signature map (after PCA mapping). In particular, we calculate the inter-sample distances from all sample signature maps, and then set the kernel size as the average of these inter-sample distances.

2.3. Estimating intermediate template for a test image based on learned image-deformation correlations

Given a new test image, its relative deformation to the template can be directly estimated based on the learned image-deformation correlations. *First*, the test image is linearly aligned to the template space using FSL. *Then*, the test image is transformed to be a signature map by the subsequent steps of image down-sampling and image subtraction from the template. *Afterwards*, the dimensionality of the signature map of the test image is further reduced by a PCA space that has been trained by all sample signature maps in the above. *Finally*, based on the learned image-deformation correlations, we can immediately estimate the deformation coefficients for the test image. By using the estimated deformation coefficients, we can use equation (1) to construct a dense deformation field, and use it to warp the template image for obtaining an intermediate template for the test image.

2.4. Registering intermediate template with the test image

In the previous subsections, we have described how to create the intermediate template for a new test image by learning the correlation between the sample images and their respective deformation coefficients. After generating the intermediate template, we can use it as a bridge to perform image registration with the new test image.

Since the intermediate template has been placed very close to the test image, the registration can be completed very fast, e.g., using a conventional registration algorithm such as HAMMER or B-spline based registration algorithms. By connecting the deformations from the template to the intermediate template and the deformation from the intermediate template to the test image, we can finally obtain a complete deformation field from the template to the test image. By using this proposed registration method, we can perform the image registration much faster than HAMMER algorithm. For example, we can complete the registration of two brain images of the size of 256×256×124 within 20 minutes, while HAMMER needs about 2 hours to complete the same registration.

3. Experimental results

The performance of our learning-based registration method is evaluated by both real and simulated data. We use 30 brain images as training samples to construct a PCA-based statistical deformation model. This model is *first* used to generate 2610 pairs of sample shape deformations and the respective sample images. *Then*, we use our regression models to learn the correlations between the features of sample images and the respective deformation coefficients to the template. *Finally*, for a new test image, we *first* fast estimate an intermediate template using the learned correlations (between images and deformation coefficients), and *then* use the intermediate template as a bridge to fast register the test image with the template. The performance of this learning-based registration method is compared with that of HAMMER algorithm in both registration quality and computation time. All of the following experiments are performed on 3D images, with size of 256×256×124. To reduce the dimensionality of the images for effectively learning the correlation between images and deformation coefficients, signature maps are selected with a size of 32×32×15 and their dimensionality is further reduced using PCA as mentioned before.

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3.1. Experiments on simulated data

The regression models, which are used to establish the correlations between features of images and the respective deformation coefficients, are first evaluated. Fig. 3 shows the estimation errors on deformation coefficients for both training and testing data. The results on training data represent whether our regression models are able to learn what we want to learn. The results on testing data indicate the capability of the learned regression models in predicting deformations based on the given image features. It can be observed that errors on training data are smaller than those on testing data, and also errors on testing data are ranging from 3% to 15%.

We further performed several simulated experiments to check whether the errors in estimating deformation coefficients, equally the errors in estimating intermediate template, will affect the performance of final image registration. To do this, we first estimate shape deformations from the template to the selected samples. Then, we map shape deformations to the pre-constructed PCA space, therefore we can obtain deformation coefficients in the PCA space, which represent the approximation of original shape deformations in the PCA space. We use these deformation coefficients as ground-truth, and use them to generate intermediate template, called here as ground-truth intermediate template. We also add 30% error on each of those deformation coefficients, and generate new intermediate templates. We use these different intermediate templates as a bridge to perform the registration between template and the selected samples, respectively. In this way, we can evaluate whether the registration results obtained by these different intermediate templates are still similar. As demonstrated in Fig. 4, we can observe that the errors in estimating intermediate template will not affect the registration performance.

3.2. Experiments on real data

Fig. 6 demonstrates the performance of our learning-based deformation estimation method on the real brain images. Give test images (Figs. 6(a)–(e)), their intermediate templates (Figs. 6(f)–(j)) are estimated based on the learned correlations between features of images and deformation coefficients. It can be observed that the intermediate template is more similar to the test image, compared to the original template (Fig. 5).

Moreover, the final registration result (Fig. 7(c)) for the test image Fig. 6(a) is very similar to that obtained by HAMMER (Fig. 7(d)). Importantly, our method can perform the same image registration about 5 times fast than HAMMER, according to various tests on 256×256×124 brain images.

4. Conclusion

We have presented a learning-based registration method for performing fast deformable registration. Regression models are trained to capture the correlations between features of sample images and the respective deformation coefficients, generated by a PCA-based statistical deformation model. The learned correlations are used to immediately estimate the deformation coefficients, and generate an intermediate template close to the test image. Since the registration between the intermediate template and the test image is relatively easy, compared to the registration between original template and the test image, our method can perform the same registration five times fast than HAMMER algorithm. Also, the registration result is comparable to that obtained by HAMMER.

In the future, we will evaluate the performance of the proposed registration method on more real datasets, and will also improve its performance based on the evaluation results.

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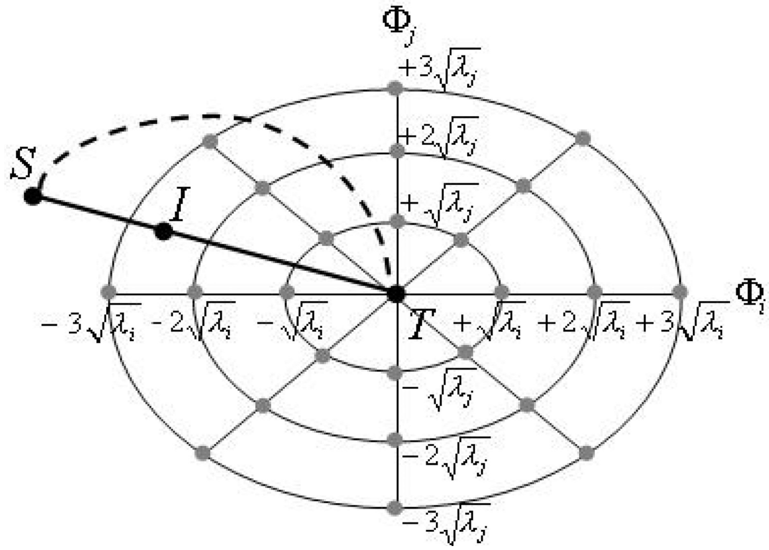

Figure 1.

The concept of the proposed registration method via an intermediate template (*I*) generated by a PCA-based statistical deformation model (solid line). In contrast, the conventional registration performs the registration between original template (*T*) and test (*S*) images directly (dashed line).

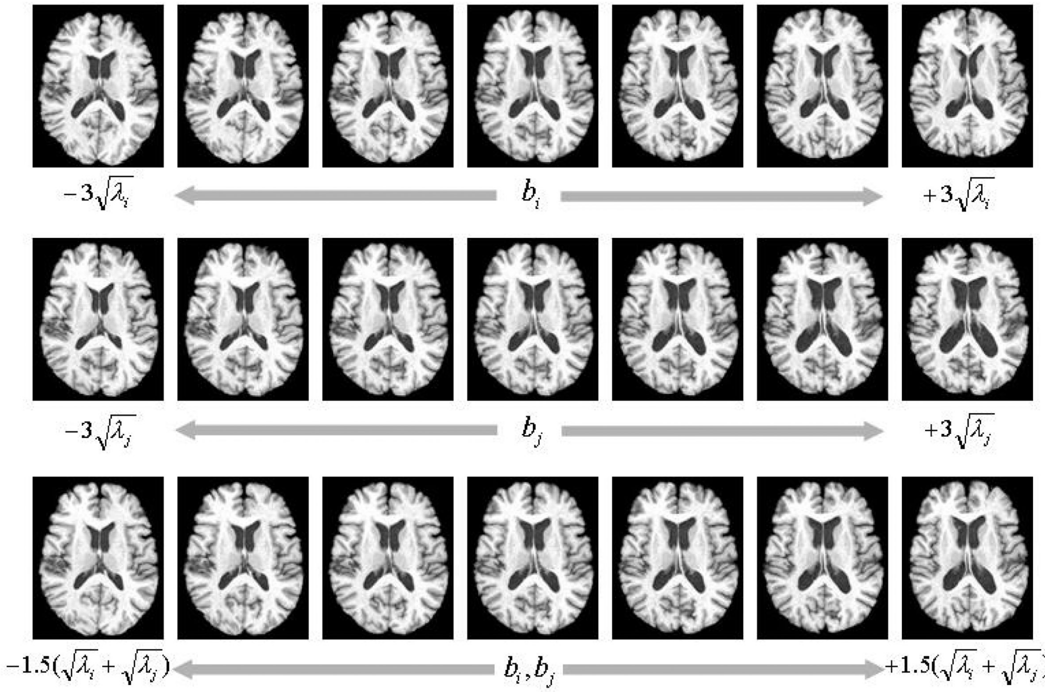

Figure 2.
Examples of sample images synthesized by the statistical deformation model.

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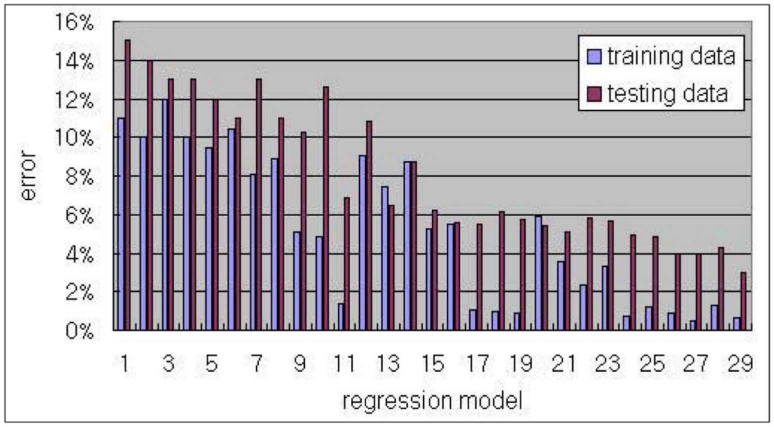

Figure 3.

The performance of trained regression models, evaluated using both training data and testing data. Note, one regression model is designed for one deformation coefficient, thus the number of registration models (e.g., 29) is equal to the total number of deformation coefficients that we want to estimate in the PCA space (e.g., also 29).

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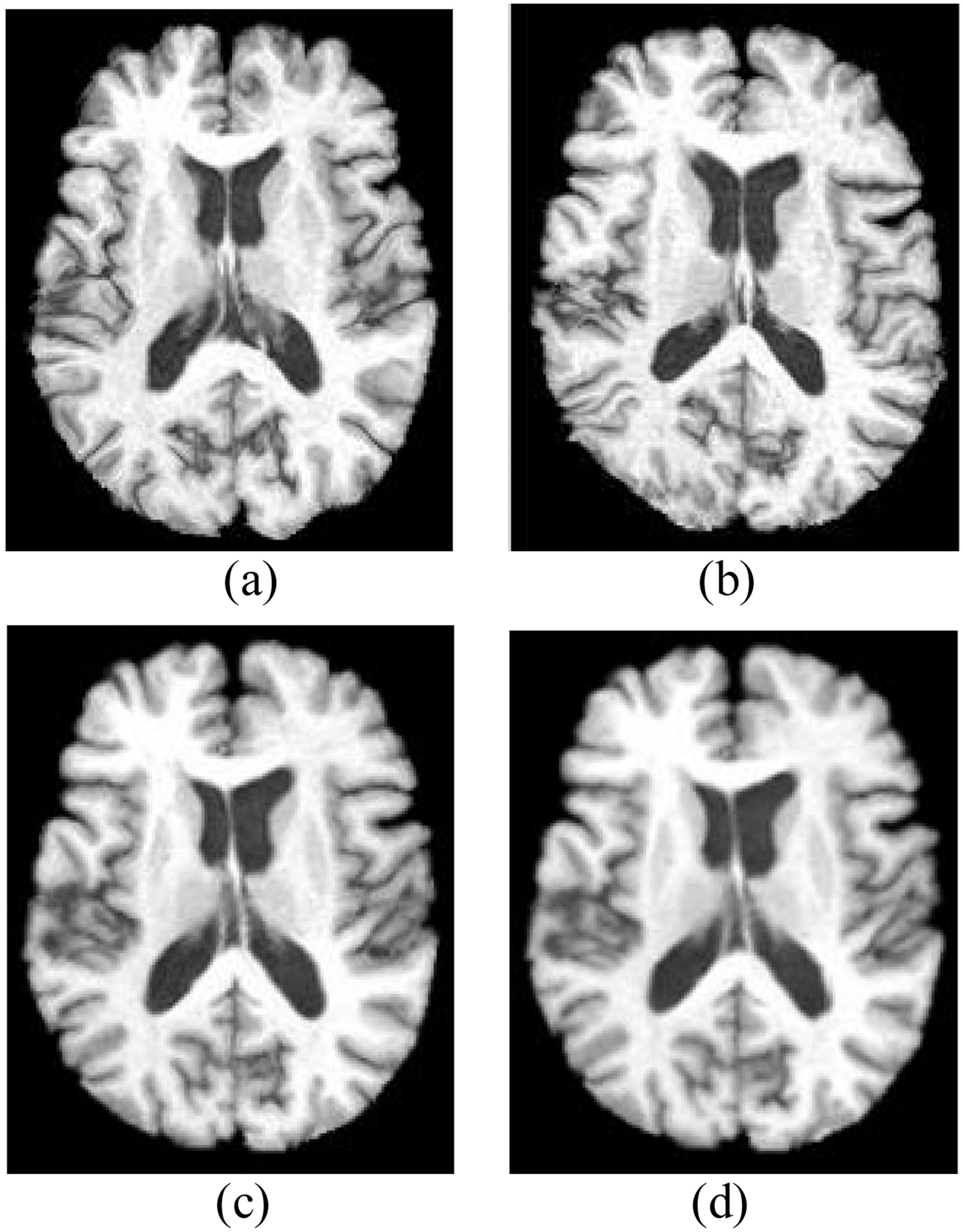

Figure 4.

Testing on whether errors in estimating intermediate template affect final registration performance. (a) A ground-truth intermediate template; (b) an intermediate template estimated with 30% errors in each deformation coefficient. (c) Registration result using an intermediate template in (a); (d) registration result using an intermediate template in (b). As we can observe, these registration results are pretty similar.

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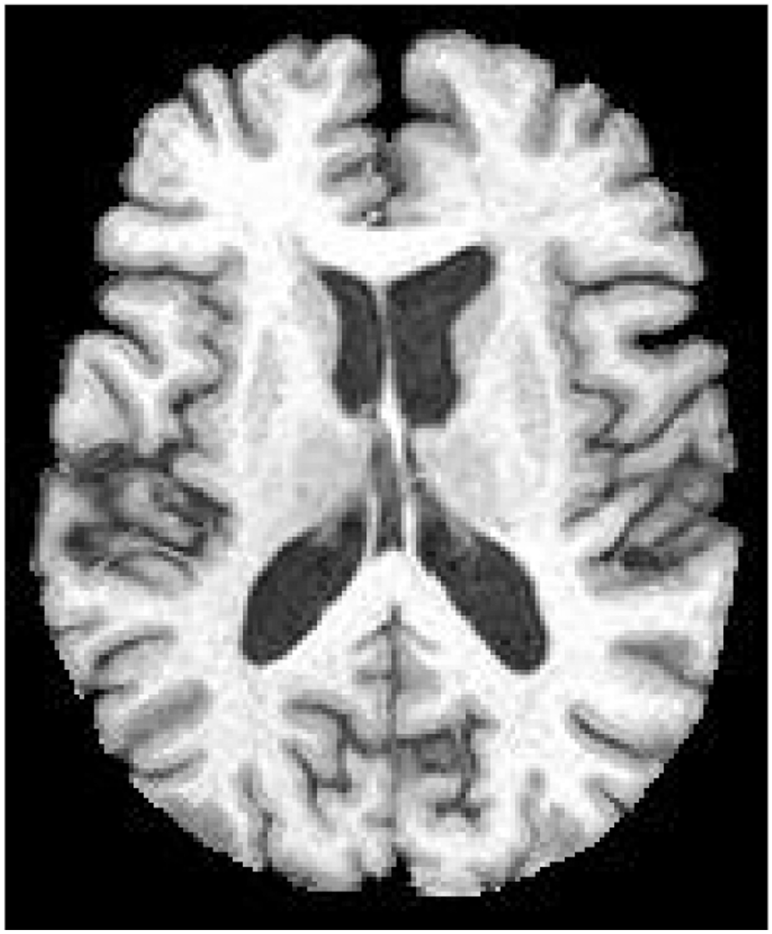

Figure 5.
Template image.

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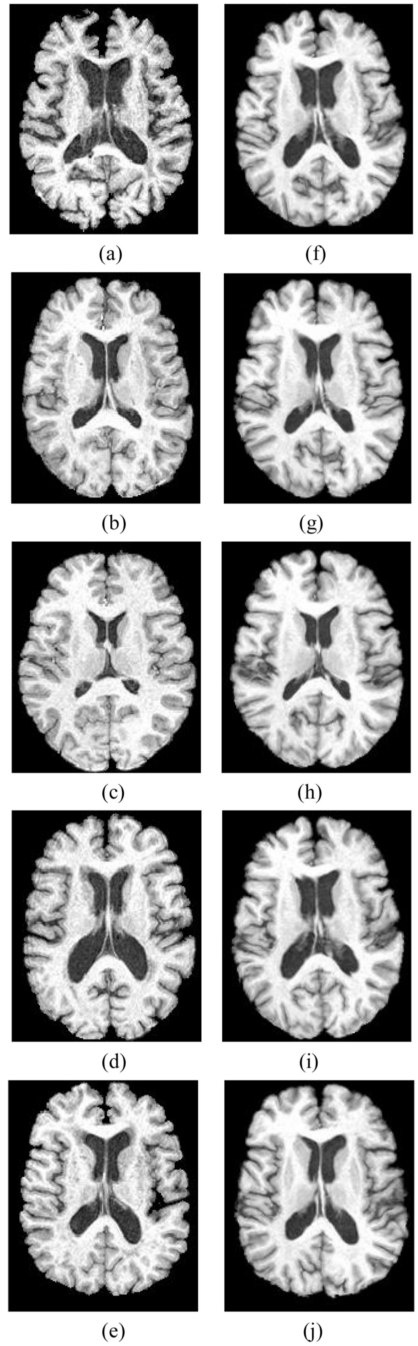

Figure 6.
The performance of estimating intermediate templates. (a)–(e) Test images; (f)–(j) the estimated intermediate templates for each test image (a)–(e).

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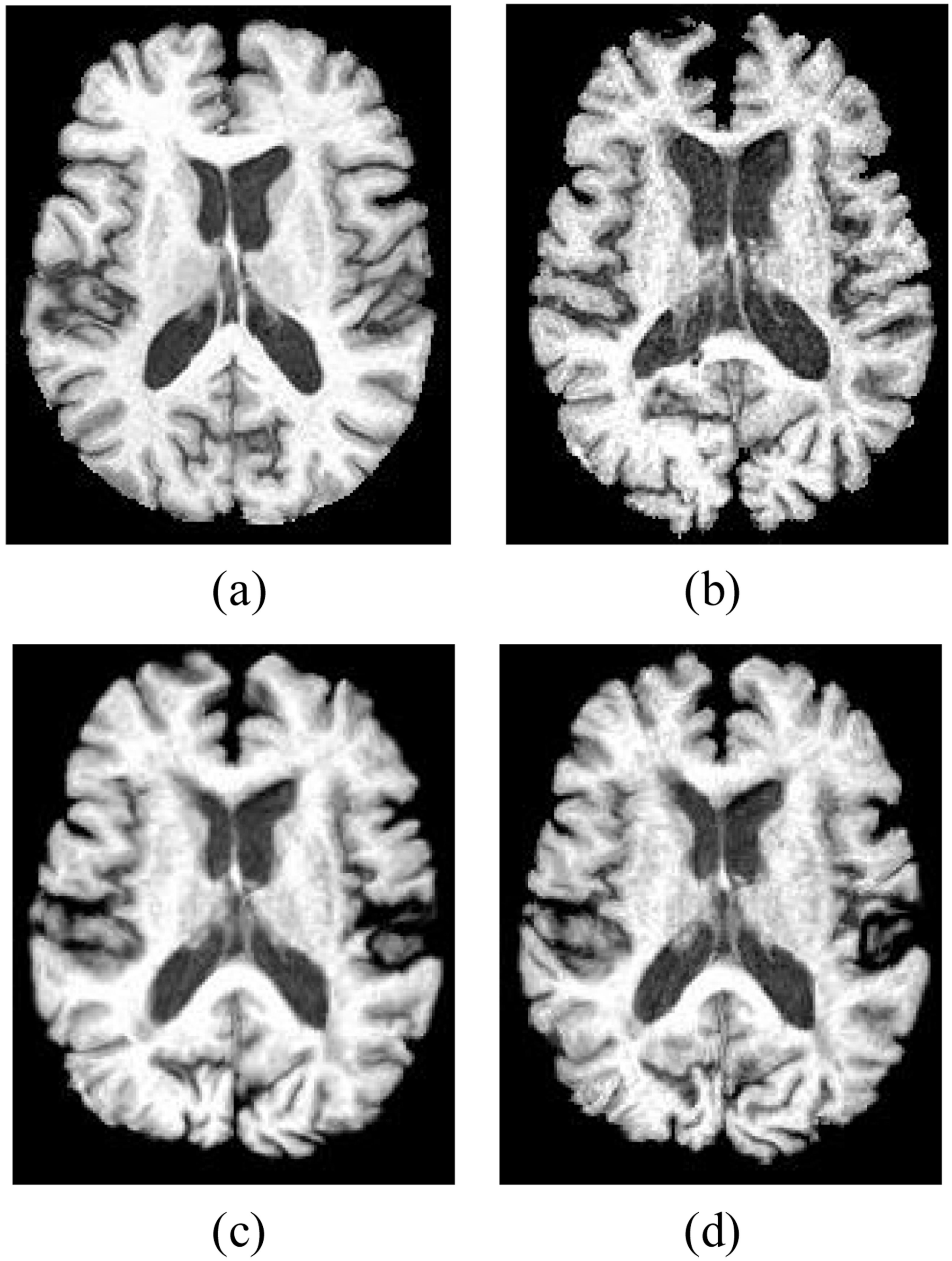

Figure 7.

Registration results of our proposed method. (a) Template image; (b) test image; (c) the registered test image in the template space by our method; (d) the registered test image by HAMMER.