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Geometric Distortion Correction for Echo Planar Images Using Nonrigid Registration with Spatially Varying Scale

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Abstract

One method used to correct geometric and intensity distortions in Echo Planar images is to register them to undistorted images via nonrigid deformations. However some areas in the Echo Planar images are more distorted than others, thus suggesting the use of deformations whose characteristics are adapted spatially. In this paper, we incorporate into our previously developed registration algorithm a spatially varying scale mechanism, which adapts the local scale properties of the transformation by means of a scale map. To compute the scale map, a technique is proposed that relies on an estimate of the expected deformation field. This estimate is generated using knowledge of the physical processes that induce distortions in EPI images. We evaluate the method of spatially varying scale on both simulated and real data. We find that, in comparison with our earlier method using fixed scale, our new method finds deformation fields that are smoother and finds them faster without sacrificing accuracy.

Keywords

Nonrigid registration; spatially varying scale; distortion correction; echo planar images; regularization

1. Introduction

Echo Planar Imaging (EPI) is known for its ability to acquire magnetic resonance (MR) images in a very short time. It has been widely used in many applications, such as functional imaging, diffusion imaging and perfusion imaging. However, EPI images are known to be prone to geometric and intensity distortions. Nonrigid registration-based methods have been used to correct for these distortions [1]–[5]. Such methods, by registering an EPI image to a reference image with no distortion or negligible distortion, generate a deformation field that is then applied to the EPI image to produce a corrected one. Because these methods often rely on deformations with a very large number of degrees of freedom, their regularization is of great importance for their accuracy, robustness, and speed.

A number of techniques have been used to regularize the deformation field. One approach is to regularize the field *uniformly*. In [6], a penalty term, related to the second derivative of

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the deformation field, is added to the cost function to constrain the transformation to be smooth. Rohlfing *et al.* [7] propose volume-preservation transformations, which are achieved by introducing a term that penalizes transformations whose Jacobian is different from one. In [8], [9], a stationary Gaussian filter is used to smooth the deformation field after each update in a demon-based registration algorithm. In [10], a constraint is applied to the relative value of the coefficients of adjacent basis functions to keep the Jacobian of the transformation positive definite. In many situations, however, the characteristics of the deformation are spatially dependent due to intrinsic properties of the images to be registered. For example, in images consisting of hard tissue and soft tissue, the former is expected to remain more rigid than the latter. A priori information about the deformation can be used to *adapt spatially* the regularization of the deformation fields and methods to do so have been proposed recently. In [11], a robust estimator is used on the regularization term to take into account possible discontinuities of the deformation field in a registration method based on optical flow. In [12] a modified viscous-fluid algorithm is proposed to reduce or prohibit deformations in specific areas based on an initial segmentation. Duay *et al.* [13] assign different values to a stiffness parameter used in the method described in [10] for image regions with different properties, thereby permitting the spatial adaptation of the transformation characteristics. In [14], three constraints on the Jacobian of the local deformation field inside a pre-generated mask are proposed to preserve the rigidity of the transformation on vessels. Li *et al.* [15] add an additional term in the cost function for minimizing the displacement of bone structure and use it for whole body registration. Stefanescu *et al.* [16] employ two non-stationary regularization steps in a demon-based algorithm. They apply diffusion equations to both the intermediate correction field and the overall deformation field. The image gradient and information on structures in the images are used to provide values for the parameters in the diffusion equations. In [17], an idea similar to the one in [16] is employed to build a statistical stiffness map for the deformation field.

When basis functions are used for parameterizing the deformation field, the support size of each basis function also affects the regularization of the deformation field. Smoothness of the deformation field is intrinsic at scales smaller than the support size. To accommodate local deformations, a high density of basis functions with a small support size is needed. But, relying on a dense regular grid of basis functions leads to a complex optimization problem with a very large number of degrees of freedom. In recent years, approaches have been proposed to address this problem. For instance, Rohde *et al.* [10] put basis functions on a regular grid first and then identify mismatched regions based on the gradient of the cost function with respect to the coefficients of these basis functions. Control points are then placed only on these regions and are optimized separately. In [18] and [19], local entropy is used to identify active and inactive regions, and only control points in the active regions are allowed to be changed during the optimization. Similarly, Park *et al.* [20] identify those mismatched regions based on local Mutual Information (MI) and entropy measures, and they add one control point each time at the location where the maximum local mismatch occurs. While these adaptive registration methods reduce the optimization complexity, the detection of mismatched or active regions is typically done at the same scale over the entire image. This not only is time consuming but also assumes that the properties of the transformation do not change spatially. This assumption may lead to spurious local displacements due to local optima in regions in which the deformation field ought to be smooth and regular. The use of a priori information to constrain the deformation fields may help to alleviate the problem. Recently, Pekar *et al.* [30] propose a method in which the scale of the transformation is adapted spatially. They apply Gaussian-shaped forces at control points and use a PDE (Navier equation) to model the connection between the forces and the resulting deformation field. The influence areas of the forces, i.e. the Gaussian width σ , are adjusted automatically together with their strengths and the positions of the control points during the

optimization. While, as claimed by the authors, the method can achieve similar results by using less control points than the registration methods based on regular grids, the optimization complexity is increased because the position of the control points is a free parameter. Also, a priori information about the deformation field is not considered in their method.

In this paper, we propose an approach to integrate a priori information into our registration algorithm. We introduce a scale map into the algorithm to specify the support size of the basis functions to be used over the various regions of the image. We also present a method to compute the scale map from a priori information, namely, an estimate of the expected deformation field. Knowledge of the physical processes that induce distortion in the EPI images is used to calculate this estimate. The proposed approach is applied to both simulated and real images. The remainder of the paper is organized as follows. Section 2 describes a priori information about distortions in EPI images. Section 3 presents our approach in detail. Experiments on simulated and real data are presented in Section 4. Finally, conclusions are drawn in Section 5.

2. A priori information about distortions in EPI images

2.1 Distortions in EPI images

It is known that geometric distortion in EPI images in the presence of an inhomogeneous main magnetic (B_0) field is directed almost exclusively along the phase encoding direction (here the y direction)[25]. Thus, the displacement at location (x, y, z) can be written as

$$\mathbf{D}(x, y, z) = [0 \quad \Delta y(x, y, z) \quad 0]^T \quad (1)$$

where $\Delta y(x, y, z)$ is the geometric distortion at the original position (x, y, z) and is calculated by:

$$\Delta y(x, y, z) = \gamma \Delta B(x, y, z) \text{FOV}_y / \text{BW}_y. \quad (2)$$

Here, γ is the gyromagnetic ratio, ΔB is the perturbation of the B_0 field, and FOV_y and BW_y are the Field of View and bandwidth in the phase encoding direction, respectively.

Intensity distortion arising from this geometric distortion is described by a Jacobian factor:

$$J^{-1}(x, y, z) = (1 + \partial \Delta y(x, y, z) / \partial y)^{-1}. \quad (3)$$

Additionally, for Gradient Echo (GE) EPI images, signal attenuation due to intra-voxel dephasing in the through-slice direction (here the z direction) is given by:

$$h(x, y, z) = |\text{sinc}(\pi \gamma v_z t_{\text{TE}} (\partial \Delta B(x, y, z) / \partial z))| \quad (4)$$

with v_z the voxel size of the EPI image in the z direction and t_{TE} the echo time. From (2) – (4), the distortion model in EPI images can be written as:

$$i(x, y + \Delta y, z) = i_0(x, y, z) \cdot J^{-1} \quad (5)$$

or

$$i(x, y + \Delta y, z) = i_0(x, y, z) \cdot J^{-1} \cdot h. \quad (6)$$

Here, i and i_0 are images with and without distortions, respectively. (5) holds for Spin Echo (SE) EPI images, which have no signal loss caused by intra-voxel dephasing effect, and (6) holds for GE EPI images. They have been used in registration based distortion correction methods for SE EPI images [1] and GE EPI images [23], respectively.

2.2 Characteristics of the geometric distortion

According to (2), the amount of geometric distortion is proportional to the amplitude of the B_0 field inhomogeneity ΔB . Such inhomogeneity is induced mainly by the magnetic susceptibility differences between substances within the subject inside the scanner. In this paper we focus on the EPI images for human brain. In the brain, there exist mainly two substances which have very different susceptibility: air and water (i.e. soft tissue). The magnitude of the distortion typically changes smoothly in the areas inside the brain but dramatically at the interfaces between air and tissue. Because of this, we classify the existing geometric distortions as one of two types: low or high.

An example of the geometric distortion that can be observed in a real EPI image is illustrated in Figure 2. Figure 2 (a) is one slice of a high-resolution, multi-shot image volume. We call this image an “anatomic image” because of the anatomical detail it shows, and we note that geometrical distortion is negligible throughout this volume because of the multi-shot protocol used in its acquisition. Figure 2 (b) is an EPI image of the same subject. Figure 2 (c) is the corresponding geometric distortion map for the EPI protocol derived from a measured field map via (5). Profiles along the phase encoding direction, which is vertical in Figure 2 (c), are shown in Figure 2 (d) to demonstrate various types of changes across the image. By comparing the values in the three different plots in Figure 2 (d), it can be seen that a large amount of variation is present in the frontal area of the brain (from the 20th to the 60th pixel, where numbers increase downward), whereas the changes are substantially smaller inside the brain (from the 60th to 110th pixel).

3. Distortion correction via nonrigid registration with spatially varying scale

3.1 Adaptive Bases Algorithm (ABA) with spatially varying scale

Our approach is based on a previously proposed nonrigid registration method -- the Adaptive Bases Algorithm (ABA) [10]. In this section, we first describe briefly the ABA method and then introduce the way to incorporate into it a spatially varying scale mechanism.

3.1.1 Overview of ABA method—The ABA method models the deformation field, $\mathbf{D}(\mathbf{x})$, as a linear combination of a set of radial basis functions (RBFs), as shown in (7):

$$\mathbf{D}(\mathbf{x}) \equiv \mathbf{x}' - \mathbf{x} = \sum_{i=1}^n \mathbf{c}_i \Phi(\mathbf{x} - \mathbf{x}_i) \quad (7)$$

where, $\mathbf{x}'$ and $\mathbf{x}$ are corresponding locations in units of voxels in two images to be registered, and $\Phi(\mathbf{x} - \mathbf{x}_i)$ is a scalar basis function centered at location $\mathbf{x}_i$ with vector coefficient $\mathbf{c}_i$. (A bold math font signifies a three-element vector.) Furthermore, $\Phi(\mathbf{Y}) = \phi(\|\mathbf{Y}\|_2/a)$, where $\|\cdot\|_2$ is the Euclidean norm, a is the size of the support of the basis function, and $\phi(\cdot) = \phi_k, j(\cdot)$, with $k=1$ and $k=2$, is one of Wu's compactly supported RBF [28]. An optimum transformation is obtained by finding the coefficients of the basis functions that maximize the normalized mutual information [29] between the images. In a typical application, registration is performed in a multilevel approach by progressively changing the resolution of the images and the support size of the basis functions. A particular combination of image resolution and basis function density is called a “level”. (In this algorithm, the

support size of the basis functions is inversely proportional to their density, i.e. when the density increases by some factor, the size of the support decreases by that same factor). At each level, a set of basis functions with the appropriate density is first placed on a regular grid. The gradient of the similarity measure with respect to the coefficients of the basis functions is computed and used to identify regions of mismatch. These regions are then optimized independently. The process is repeated until the highest image resolution and highest density of basis functions is reached.

3.1.2 $\mathbf{d}_{\text{final}}$ and Scale map—In the ABA method, the scale of the transformation is controlled by the density of basis functions at the final level, which we call $\mathbf{d}_{\text{final}}$ (it is a 1×3 vector containing the densities in the x, y, and z directions). When $\mathbf{d}_{\text{final}}$ is low for a given region, few basis functions with a large support size are used, which leads to transformations that are smooth and regular everywhere within the region. On the other hand, a high $\mathbf{d}_{\text{final}}$ permits the modeling of highly local deformations with a large number of degrees of freedom. Such a model allows almost arbitrary deformations, corresponding to a weak regularization. Hence, $\mathbf{d}_{\text{final}}$ can be viewed as a regularization factor which determines the scale of a deformation field. To adjust $\mathbf{d}_{\text{final}}$ spatially, a scale map S , which is a volume that has the same size as the image, is introduced into the ABA algorithm as a new component. According to S , a higher $\mathbf{d}_{\text{final}}$ is assigned to the regions where we anticipate rapid variations in the deformation field, and a lower $\mathbf{d}_{\text{final}}$ is assigned to regions where slow variations are expected. In a multi-level approach, all the levels up to the pre-specified $\mathbf{d}_{\text{final}}$'s will be used for the regions with different scales in the registration. The method we use to generate S is described in the following section.

3.2. Distortion correction approach

The main steps in our distortion correction approach are shown in Figure 1. Among them, Step 3 has been introduced in Section 3.1. Step 1 and 2 are presented in this section.

3.2.1 Generation of scale map—Based on a priori information about the expected deformation field, a number of strategies can be used to generate a scale map. One could assign manually a scale to a given location in the scale map, but this requires the scale information for each location to be known a priori. When such information is not available a priori, it needs to be computed. One solution, in this case, is to use an estimated deformation field and to extract scale information from that field. The estimated field can be derived from a deformation field computed from a large population, as in [17] and [24], or it can be generated using knowledge about the problem at hand, which is the approach we follow in this paper. Here, we present a technique to compute a scale map from an estimated deformation field. The generation of this field is based on knowledge about the physics of EPI, which is described in Section 3.2.2.

To compute a scale map of a given deformation field $\mathbf{D}_0$, we need to determine areas in the field that are smooth and slowly varying and areas in which changes are faster. The approach we use to do this is similar to the multilevel scheme we use in the ABA algorithm and summarized as follows:

1. Pre-specify a RBF array Θ , the number of scales and the level of RBF that define each scale.
2. Fit $\mathbf{D}_0$ iteratively with each level of RBF in Θ .
3. For a level of RBF that define a scale:
 1. Identify the regions in $\mathbf{D}_0$ that can be fitted well by using RBF up to this level;

2. Set the value at the corresponding regions in the scale map as this level of RBF.

Conceptually, we fit the field, first with a few basis functions with large support, then with more and more basis functions with smaller and smaller support. If the field changes slowly, the fitting is good enough with few basis functions. When the field changes rapidly, more basis functions are necessary. Practically, we store in an array $\Theta = [(N_{x1}, N_{y1}, N_{z1}), (N_{x2}, N_{y2}, N_{z2}), \dots, (N_{xn}, N_{yn}, N_{zn})]$ the numbers of basis functions we use in the x, y, and z directions at each iteration. The density of basis functions corresponding to level j is then $\mathbf{d}(j) = \Theta[j]/\mathbf{V} = (N_{xj}/v_x, N_{yj}/v_y, N_{zj}/v_z)$, where $\mathbf{V} = (v_x, v_y, v_z)$ is the size of the image in the x, y, and z directions. The values in each direction increase monotonically from the beginning to the end of the array. Here, n , the length of Θ , is the number of iterations we use when fitting the field. Given a deformation field $\mathbf{D}_0$, we do the following at the m^{th} iteration:

Step 1: Set the current deformation field, $\mathbf{D}_{\text{current}}(\mathbf{x}, m)$, as the residual deformation field obtained from the previous iteration $\mathbf{D}_{\text{residual}}(\mathbf{x}, m-1)$, i.e.

$$\begin{aligned} \mathbf{D}_{\text{current}}(\mathbf{x}, m) &= \mathbf{D}_{\text{residual}}(\mathbf{x}, m-1) \\ \mathbf{D}_{\text{residual}}(\mathbf{x}, 0) &= \mathbf{D}_0(\mathbf{x}) \end{aligned} \quad (8)$$

Step 2: Use RBFs at level m (i.e. with total number $N_m = N_{xm} \times N_{ym} \times N_{zm}$) to approximate $\mathbf{D}_{\text{current}}(\mathbf{x}, m)$ with a least-squares approach. A new residual deformation field $\mathbf{D}_{\text{residual}}(\mathbf{x}, m)$ is computed as:

$$\mathbf{D}_{\text{residual}}(\mathbf{x}, m) = \min_{\mathbf{C}(\Omega)} \sum_{\mathbf{x} \in \Omega} \left[\sum_{j=1}^{N_m} \mathbf{c}_j \Phi(\|\mathbf{x} - \mathbf{x}_{j,m}\|) - \mathbf{D}_{\text{current}}(\mathbf{x}, m) \right]^2 \quad (9)$$

where Ω represents the entire image space, and $\mathbf{x}_{j,m}$ is the spatial location of the j^{th} basis function at level m , and $\mathbf{c}_j \in \mathbf{C}(\Omega)$ is the coefficient of the j^{th} basis functions.

After all $\mathbf{D}_{\text{residual}}(\mathbf{x}, m)$, $1 \leq m \leq n$ are obtained, the scale map can be computed by selecting a number of scales and thresholding the corresponding $\mathbf{D}_{\text{residual}}$. One could use as many scales as entries in the Θ array. But, this would be impractical. Often the nature of the problem dictates the number of scales to be used. For instance, in the application described herein, two scales, named low scale and high scale, are sufficient to model the deformation field (see Section 3.1 for details). We then empirically decide the density of basis functions that define the low and the high scale. $\mathbf{d}(3)$ could, for instance, specify the density of basis functions we want to use to model the field at the low scale. We examine the value in $\mathbf{D}_{\text{residual}}(\mathbf{x}, 3)$ after $\Theta(3)$ basis functions are used in the fitting. Areas in $\mathbf{D}_{\text{residual}}(\mathbf{x}, 3)$ for which the value is below a threshold is considered to be approximated well by using basis functions with density up to $\mathbf{d}(3)$. The corresponding areas in the scale map $\mathcal{S}$ are then labeled as low scale and assigned the value 3. The other areas are labeled as high scale and assigned the value n . When registering the images, we use the same array Θ to specify the density of the basis functions used at each level. Following our example, $\mathbf{d}_{\text{final}}$ will be set to $\mathbf{d}(3)$ in the low scale areas and to $\mathbf{d}(n)$ in the high scale areas. This instructs the registration algorithm to use basis functions with densities up to $\mathbf{d}(3)$ in the low scale areas and up to $\mathbf{d}(n)$ in the high scale areas.

3.2.2 Estimation of the distortion field in EPI images—As described in Section 3.2.1, we calculate a scale map based on $\mathbf{D}_0(x, y, z)$, an estimate of the expected deformation field. In our application, $\mathbf{D}_0(x, y, z)$ can be generated based on knowledge of the physical phenomena affecting the images. To generate $\mathbf{D}_0(x, y, z)$, we segment the anatomic image of a subject into air and water using a simple thresholding method. The threshold in this

method is selected based on the histogram of the image. The obtained binary image is further processed by morphological ‘dilate’ and ‘erode’ operations to remove small gaps or speckles. A water/air susceptibility map is created based on this binary image and then convolved with a kernel to generate a simulated field map using the method described in [21]. A distortion field at each location (x, y, z) is computed from this field map and used as the y component of $\mathbf{D}_0(x, y, z)$, which is 0 in the x and the z components, as shown in (1). Note that accurate simulation of the field map is a complicated task in itself [21], [22], [27], and it requires precise head models. To initiate our scale map calculation, however, we need only a rough approximation. More specifically, the estimated deformation field is expected to have similar variations as in the real one, and the amplitude of the estimated deformation field at each location doesn’t need to be accurate.

4. Experiments and Results

In this section we describe experiments in which we evaluate our method and show how it compares to our previous approach in which a uniform scale is used, which we call the “fixed scale” approach. We apply it to both simulated and real 3D EPI images, which contain geometric and intensity distortions. The smoothness, accuracy, and running time of the algorithm with and without spatial scale adaptation are compared.

4.1 Parameters for the scale map

In the set of experiments conducted with both simulated and real EPI images, we experimentally choose a RBF array Θ with 6 levels to compute the scale map. The same Θ is also used in our registration process. We select the 4th and the 6th RBF densities (i.e. $\mathbf{d}(4)$ and $\mathbf{d}(6)$) as the $\mathbf{d}_{\text{final}}$ ’s for the low and the high scales, respectively. Figure 3 shows an example of a given deformation field (a) and the corresponding scale map (b) obtained with these parameters. As expected, the low scale region mainly corresponds to area inside the brain while most of the high scale region is located in the frontal part of the image, close to the sinuses. Note that for simulated EPI images, we compute each scale map from the deformation field derived from a measured field map; for real EPI images, we compute each scale map using an estimate of the distortion field obtained with the method described in Section 3.2.2.

4.2 Experiments with 3D simulated and real EPI images

4.2.1 Simulated GE EPI images—In this section, simulated GE EPI images are used to evaluate the proposed method. A $256 \times 256 \times 28$ T1-weighted head image volume of each of six subjects is acquired using a Philips 3T MR scanner. A field map for each of the subjects is also acquired during the same study from the phase difference between two Fast Field Echo (FFE, gradient echo) scans collected at differing echo times. The field map has the same dimensions and voxel size as the T1-weighted image. Using our MR simulator [21], six distortion-free EPI volumes (size $128 \times 128 \times 12$) corresponding to the six subjects are generated. The input to the simulator consists of three tissue volumes: white matter, gray matter, and CSF, which are segmented from each of the six T1-weighted images. Figure 4(a) shows a typical slice in a distortion-free image volume.

We then use these reference images and the measured field maps to create six simulated EPI images with geometric distortion and modified intensity values according to (6). The distorted version of Figure 4(a) is shown in Figure 4(b). The geometric distortions computed from the field maps are used as the ground truth to which the deformation fields obtained with our method are compared. The distortion model given in (6) is included in our registration method as described in [23]. The registrations are performed using three approaches: fixed low scale (i.e. use level 1–4 in Θ everywhere), fixed high scale (i.e. use

level 1–6 in Θ everywhere) and spatially varying scales (i.e. a scale map with value 4 and 6). Figure 4(c) shows the image in Figure 4(b) after it has been corrected with our spatially varying scale approach. Figure 4(d) and (e) are the intensity differences, (b)–(a) and (c)–(a), respectively; these show a substantial reduction in both geometric and intensity distortions after correction.

Figure 5 compares the residual errors, inside the low scale region (a) and the high scale region (b), of the deformation fields estimated with both the fixed low scale and the fixed high scale approaches. The errors are computed as the mean absolute difference (MAD) between the estimated deformation fields and the ground truth. It can be seen that in the low scale region increasing the density of the basis functions does not substantially affect accuracy. However, increasing their density improves accuracy in the high scale region. Although using radial basis functions with high density everywhere in the image may appear to be a solution, it is not ideal. There are indeed several disadvantages in using high density when it is known to be unnecessary. First, computation time increases. Second, the algorithm may over fit the data. As will be shown in the next section in which real images are used, using too many degrees of freedom in regions where it is not needed leads to deformation fields that are not as smooth as what would be expected from our knowledge of the physical process (this problem is not as apparent with the simulated images we use in this section because they are themselves smoother than the real ones).

Figure 6 shows the residual errors over the entire deformation field when the fixed high scale and the spatially varying scale approaches are used. These results show that, with the data used in this section, the spatially varying scale approach leads to an accuracy that is comparable to the fixed high scale approach. However, as shown in Table 1, it does it in a fraction of the time.

4.2.2 Real GE EPI images—In this section, the spatially varying scale scheme is evaluated with real GE EPI images of six subjects. For each subject, a set of GE EPI images and a single high-resolution, multi-shot, spin-echo anatomic image are acquired on a Philips 3T scanner. The image resolution for the GE EPIs is 128×128 (interpolated from 80×80), with 12 slices, TE 35 ms, voxel size $1.875 \times 1.875 \times 4.5$ mm, with 0.4mm gap. The anatomic images have the same number of slices as the GE EPIs but have 256×256 in-plane resolution. They are downsampled to 128×128 for registration purpose. See Figure 7 (a) and (b) for an example. Note that the non-brain tissue in each image is removed using a brain extraction tool [26]. As can be seen, the geometric distortion and intensity attenuation are present mainly in the frontal regions of the brain. Each GE EPI image is registered to its corresponding anatomic image using the proposed method to correct for geometric distortion and signal loss.

Figure 7 (c) and (d) show the images after correction using nonrigid registration methods with fixed (high) scale and spatially varying scale, respectively. The iso-intensity contour of the brain is outlined in (a) and overlaid onto the other images. Both approaches lead to similar results albeit the spatially varying scale method seems able to recover more signal in the area above the ventricles (shown with white arrows in the figure).

The smoothness and regularity of the deformation fields obtained with our approaches is illustrated in Figure 8 and Figure 9. Figure 8 (a) and (b) show examples of the deformation fields obtained with the fixed scale and the spatially varying scale approaches, respectively, for all six subjects. In all cases, the deformation fields obtained with both approaches are qualitatively similar, but the varying scale approach leads to smoother fields. Figure 8 (c) and (d) show 3D views of the magnitude of the deformation field over the rectangular windows drawn in Figure 8 (a) and (b). To evaluate the smoothness of the deformation

fields (12 in total) over the entire image volume, the Laplacian of each deformation field is computed, summed over the volume, and normalized. Figure 9 plots this value for the 6 volumes that have been used to evaluate our method. Using spatially varying scales leads to a reduction on the order of 13%. Timing information for both approaches is provided in Table 2, which shows a substantial amount of reduction for the spatially varying scale method.

5. Discussion

Regularizing deformation fields obtained with nonrigid registration algorithms is a difficult issue. Too much regularization leads to inaccuracies. Too little regularization leads to spurious and physically unlikely deformation. Results presented in this paper show that this is the case for EPI images. Excessive regularization leads to transformations that are inaccurate in areas where the magnetic field changes rapidly. Using a regularization scheme that leads to good results in these areas, e.g. basis functions with small support everywhere, unfortunately leads to transformations that are not as smooth as expected in areas where the field changes slowly. This paper proposes a novel approach in which the regularization of the field is adapted spatially by means of a scale map. We also introduce a method by which this scale map can be generated according to a priori information. Our experimental results show that the proposed approach leads to transformations that are smoother and that can be computed faster than those computed when a fixed scale is used without sacrificing accuracy.

In the ABA method, the scale of the regions of mismatch is detected automatically by employing a multi-scale approach, in which up to the highest level of basis functions is applied to the area over the whole image. There is no a priori information incorporated. As a consequence, for regions over which the deformation fields change slowly, i.e., regions for which less than the maximum density of basis functions is required, unnecessary computations will be performed. In addition, as discussed before, spurious local displacements due to local optima in these regions may be introduced. The proposed approach addresses these problems.

As described in the Introduction section, spatially varying scale based on a priori information was also employed in [16], [17]. Their method implements such scheme by applying a non-stationary diffusion filter to the obtained displacement field. The diffusion parameter in the diffusion filter is computed based on the knowledge on the deformability of segmented tissues. Instead, according to a pre-computed scale map, we specify the support size of basis functions used for different areas before the registration process.

Clearly, the generation of the scale map and of the expected deformation field carries a computational overhead. In our experiments, the scale map computation itself can be done in about 40 seconds; computation of the field map takes about 50 seconds. If these are included in the total computation time, then the spatially varying scale method loses its computational advantage for the correction of a single volume. However, in practice, the scale map needs to be computed only once for an fMRI study, which may involve more than a hundred volumes. In this case, the method we propose is advantageous. For illustration purposes, we consider registrations on an fMRI dataset with one hundred volumes. The running times for the fixed scale and the spatially varying scale approaches (on a PC with a 3.0G Hz CPU and 1GB of RAM) are 315 min and 208 min, respectively, which represent a 34% reduction in time.

As mentioned at the beginning of Section 3.2.1, a number of ways could be used to compute the scale map. Given an estimated distortion field, a scale map could be, for example, simply

generated by thresholding the magnitude and gradient of the distortion. The main disadvantage with such an approach is the fact that the correspondence between regions and the scale of the deformation is lost. One would then need to determine which scale needs to be used over the various regions. The advantage of our approach is that the scale at which the deformation needs to be estimated is obtained directly from the fitting process. Because the scale map needs to be estimated only once to correct an entire study, the computational overhead associated with our approach is acceptable.

The main parameters that need to be selected include the length of the array Θ , the number of basis functions to be used at each level, and the number of scales to be used in the scale map. The application often suggests the number of scales to use. The length of the array and the number of basis functions to use at every level typically require experimentation when the method is applied to a new type of image. In our experience, when a set of parameter is chosen for one application and one type of image, the same set of parameters can be used across volumes.

Thanks to our simulated images, we are able to show quantitatively that our method holds promise on single EPI image volumes. Further studies will investigate the effect of our correction algorithm on fMRI time series and determine whether or not correction modifies the location and extend of areas of activation.

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Figure 1.
A flow chart for our approach.

Figure 2.

Anatomic image (a) and EPI image (b) of a subject are shown. (c) is the corresponding geometric distortion map. Profiles of distortion in units of voxels in the phase encoding direction in (c) are shown in (d). The positive horizontal direction in (d) corresponds to the downward direction in (c) in voxels.

Figure 3.
(a) Distortion field; (b) scale map with low scale in the black area and high scale in the white areas.

Figure 4.

(a) Simulated distortion-free EPI image; (b) distorted version of (a); (c) corrected version of (b) using the proposed method; (d) difference image: (b)–(a); (e) difference image: (c)–(a).

(a)

(b)

Figure 5.

Initial displacement and residual errors for 3D simulated images inside the low scale region (a) and the high scale region (b) using the fixed low scale and the fixed high scale approaches. Here the initial displacement is the mean absolute value of the ground truth of the distortion.

Figure 6. Initial displacement and residual errors for 3D simulated images over the entire deformation field using the fixed high scale and the spatially varying scale approaches. Here the initial displacement is the mean absolute value of the ground truth of the distortion.

Figure 7.

(a): anatomic image; (b): EPI image; (c) and (d): corrected images using nonrigid registration with fixed scale (c) and spatially varying scale (d). More signal recovery is apparent in some places (arrow) with spatially varying scale.

Figure 8. Estimated distortion fields for 6 subjects using fixed scale (a) and spatially varying scale (b). (c) and (d) show the magnitude of the estimated deformation field inside the blue rectangles in (a) and (b), respectively.

Figure 9.
Comparison of the Laplacian magnitudes of the deformation fields.

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Table 1

Registration times for 3D simulated EPI images (min)

Subject ID	1	2	3	4	5	6
High Scale	5.03	3.75	3.63	3.38	4.87	4.68
Spatially Varying Scale	3.20	2.12	2.10	2.03	3.45	3.05
Time Reduction	36%	43%	42%	40%	29%	35%

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Table 2

Registration times for 3D real EPI images (min)

Subject ID	1	2	3	4	5	6
Fixed Scale	4.38	4.18	4.18	4.05	4.38	4.6
Spatially Varying Scale	2.81	2.85	2.47	2.4	2.6	2.58
Time Reduction	36%	32%	41%	41%	41%	44%