

## Nonrigid Image Registration Guest Editors' Introduction



Image registration is the process of determining correspondence between all points in two images of the same scene. Image analysis applications that involve two or more images of a scene often require registration of the images. Nonrigid image registration refers to a class of methods where the images to be registered have nonlinear geometric differences.

Image registration has a long history. One of the first examples of image registration appeared in the work of Roberts [33]. By aligning projections of edges of polyhedral solids with image edges, he was able to locate and recognize predefined polyhedral objects in images. Registration of entire images first appeared in the remote sensing literature. Anuta [1, 2] and Barnea and Silverman [8] developed automatic methods for registering satellite images using the sum of absolute differences as the similarity measure. Leese *et al.* [20] and Pratt [31] did the same using cross-correlation coefficient as the similarity measure. Use of image registration in computation of depth was initially pursued by Julesz [19], and then by Bakis and Langley [7], Mori *et al.* [27], Levine *et al.* [22], and Nevatia [28]. Image registration found its way to biomedical image analysis as data from various scanners that measure anatomy and function became digitally available [6, 37, 39].

Fischler and Elschlager [15] were among the first to use nonrigid registration to locate deformable objects such as human faces in images. Burr [11] later recognized handwritten characters by nonrigid registration. Bajcsy and Broit [4] developed a nonrigid registration method that could align deformed images in their entirety. In medical imaging, nonrigid registration was initially used to standardize MR and CT brain images with respect to an atlas [5, 9]. Most nonrigid image registration methods are iterative and minimize a cost or an energy function, defined in terms of the geometric and/or intensity difference between images. A smaller number of methods are based on matched feature points and use nonlinear transformation functions to align the images. The paper by Cachier *et al.* [12] in this issue classifies various nonrigid image registration methods. Further surveys and classifications of image registration methods can be found in papers by Gerlot and Bizais [18], Brown [10], van den Elsen *et al.* [38], Maurer and Fitzpatrick [26], Maintz and Viergever [25], and Lester and Arridge [21].

Most work on nonrigid registration has used medical images, and in particular brain images. The brain is of tremendous interest because of many applications in neuroscience and neurosurgery, presenting many unique challenges. Nonrigid registration of the brain is a difficult task but has many important applications including comparison of shape and function between individuals or groups [17], development of probabilistic models and atlases [23], measurement of change within an individual, and determination of location with respect to a preacquired image during stereotactic surgery [34].

The detailed nonrigid registration and comparison of brain images requires the determination of correspondence throughout the brain and the transformation of one image space with respect to another according to the correspondences.

There are three types of deformation which need to be accounted for in nonrigid brain image registration: 1) change within an individual's brain due to growth, surgery, or disease; 2) differences between individuals; and 3) warping due to image distortion, such as in echo-planar magnetic resonance imaging.

Deformations of type 1 represent an individual's brain changes during development, surgery, or degenerative process such as Alzheimer's disease, multiple sclerosis, or malignant disease. In the cases of growth and degenerative disease, the deformation is incremental and likely to be representable in terms of relatively small and smooth transformations. During

surgery, the brain deforms or shifts due to changes in pressure, fluid loss, and other factors. This shifting is also smooth and incremental. For image-guided stereotactic surgery, the correction for this deformation must be done in real-time. Physical modeling of tissue has been used extensively for this purpose. In addition, there is a more severe deformation due to the removal of tissue (and subsequent remodeling).

Deformations of type 2 are obtained when comparing anatomy between individuals. A detailed nonrigid transformation that brings brain images from different individuals into correspondence to account for differences between the brains is required. Neuroanatomic variation between individuals is usually great, particularly in the cortex. Subcortical structures vary in shape and size between individuals in a relatively smooth manner. The cortex, however, varies greatly due to differences in folding patterns (extra and missing folds, different branching patterns, etc.), which change the shape significantly, typically requiring transformations of high flexibility and making registration quite difficult. In order to compare a group of individuals, structural variation between individuals should be accounted for by registering an atlas image to each individual's image, in order to have a common coordinate system for comparison. The field of deformation morphometry applied to medicine is seeking to build on this fundamental registration step by developing meaningful descriptions of anatomical shape derived directly from the non-rigid transformations themselves. Functional differences, as seen in corresponding functional images, can also be compared in this coordinate system.

Deformations of type 3 are obtained in magnetic resonance imaging by the imaging process [35]. For example, echo planar image (EPI) data obtained in functional imaging can exhibit severe geometric distortions. The displacements are dependent on the configuration of tissue in the subject, the orientation of the subject within the scanner, and the MRI acquisition. Knowledge of acquisition physics can help constrain estimation of the deformation.

In this special issue, most recent advances in nonrigid image registration are presented. Methods for matching image features and image regions are discussed in the first four papers, surface matching is covered in the next two papers, and volume matching is discussed in the last two papers. Chui and Rangarajan [13] describe a feature-matching method that is an extension of the iterative closest point (ICP) method, determining the transformation function and the feature correspondences at the same time while minimizing an energy function. Paragios *et al.* [30] achieve the same by first aligning the feature sets globally through chamfer matching and then estimating the local deformations by local searching. Richard and Cohen [32] find feature correspondences using image intensities in a region-matching approach. Sclaroff and Isidoro [36] discuss registration and tracking of deformable objects in videos. An object is defined by a triangular mesh and the mesh is tracked from one frame to the next by minimizing an error measure. The method is demonstrated to be robust under some occlusion, change in lighting, shadows, and surface specularities. Audette *et al.* [3] describe matching of brain surfaces obtained by a range scanner and by segmentation of a volumetric MR image. The surfaces are first aligned globally by the rigid ICP method and then locally through a local ICP method. Wang *et al.* [40] describe nonrigid registration of brain surfaces using geodesic distance and curvature measures. To nonrigidly register volumetric images, Cachier *et al.* [12] extend the block-matching idea used for rigid registration [14, 29] to Gaussian windows for nonrigid registration. Lunn *et al.* [24] use a physically-based tissue deformation model to nonrigidly register images by the finite element method.

The papers in this special issue also describe various applications of nonrigid image registration. While Chui and Rangarajan [13] and Paragios *et al.* [30] mostly use synthetic images to evaluate their methods, Sclaroff and Isidoro [36] use video images, and Richard and Cohen [32] use X-ray mammography to evaluate their work. Audette *et al.* [3], Cachier *et al.* [12], Lunn *et al.* [24], and Wang *et al.* [40] all use brain images in their work. Richard and Cohen [32], Paragios *et al.* [30], and Sclaroff and Isidoro [36] describe registration of 2-D images; Audette *et*

*al.* [3] and Wang *et al.* [40] describe registration of surfaces; Cachier *et al.* [12] and Lunn *et al.* [24] describe registration of volumetric images; and Chui and Rangarajan [13] discuss registration of both 2-D and 3-D images.

Although image registration has been a very active area of research for some time, and although robust rigid registration methods have been developed [16], more work in nonrigid image registration is needed. In a number of active areas, such developments go hand in hand with the fundamental issue of defining what we mean by correspondence between inherently different spatial structures, as is the case when comparing the brain anatomy of different individuals. Such issues must be addressed in the context of the descriptions and measurements required in a particular application. To accurately register images with local geometric differences, two main goals have to be reached. First, a large number of feature point correspondences that reflect local geometric differences between the images to be registered have to be found. Second, a transformation function should be determined that can describe and interpolate the point correspondences with a highly varying density without introducing unrealistic deformations in areas where no corresponding structures exist. Point feature detection, image similarity measures and matching techniques, as well as transformation functions that work with different image modalities, image contents, magnitude and type of geometric differences between images, are still of great interest.

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