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# Nonrigid image registration: guest editors' introduction

Image registration is the process of determining correspondence between all points in two or more images of the same scene. Image analysis applications that involve multiple 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 geometric differences that cannot be accounted for by similarity (global translation, rotation, and scaling) transformations.

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 the 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 into biomedical image analysis as data from various scanners that measure anatomy and function became 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. Witkin et al. [41] formulated the general nonrigid registration problem (i.e., that of matching multiple, arbitrary-dimensional images or signals) as one of nonconvex energy minimization and solved it efficiently using a scale-space continuation method. 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

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[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].

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.

This special issue presents 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 specularity. 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 register images nonrigidly, 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] 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 register images with local geometric differences accurately, two main goals must be reached. First, a large number of feature point correspondences that reflect local geometric differences between the images to be registered must 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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## References

[1] P.E. Anuta, Registration of multispectral video imagery, Soc. Photo-Opt. Instrum. Eng. J. 7 (1969) 168–175.
[2] P.E. Anuta, Spatial registration of multispectral and multitemporal digital imagery using fast Fourier transform techniques, IEEE Trans. Geosci. Electron. 8 (4) (1970) 353–368.
[3] M.A. Audette, K. Siddiqi, F.P. Ferrie, T.M. Peters, An integrated range-sensing segmentation and registration framework for the characterization of intra-surgical brain deformations in image-guided surgery, Comput. Vis. Image Und., this issue.
[4] R. Bajcsy, C. Broit, Matching of deformed images, Proc. Int. Conf. Pattern Recognition (1982) 351–353.
[5] R. Bajcsy, R. Lieberson, M. Reivich, A computerized system for the elastic matching of deformed radiographic images to idealized atlas images, J. Comput. Assist. Tomo. 7 (4) (1983) 618–625.
[6] D.C. Barber, Automatic alignment of radionuclide images, Phys. Med. Biol. 27 (1982) 387–396.
[7] R. Bakis, P. Langley, A method for determining the height of forest trees automatically from digitized 70 mm color aerial photographs, Proc. 7th Int. Symp. Remote Sensing of Environment (1971) 705–714.
[8] D.I. Barnea, H.F. Silverman, A class of algorithms for fast digital image registration, IEEE Trans. Comput. 21 (2) (1972) 179–186.
[9] C. Bohm, T. Greitz, B.M. Berggren, L. Olsson, Adjustable computerized stereotaxic brain atlas for transmission and emission tomography, Am. J. Neuroradiol. 4 (1983) 731–733.
[10] L.G. Brown, A survey of image registration techniques, ACM Comput. Surv. 24 (4) (1992) 276–325.
[11] D.J. Burr, A dynamic model for image registration, Comput. Graph. Image Process. 15 (1981) 102–112.
[12] P. Cachier, E. Bardinet, D. Dormont, X. Pennec, N. Ayache, Iconic feature based nonrigid registration: the PASHA algorithm, Comput. Vision Image Und., this issue.
[13] H. Chui, A. Rangarajan, A new point matching algorithm for nonrigid registration, Comput. Vision Image Und., this issue.
[14] L. Ding, A. Goshtasby, M. Satter, Volume image registration by template matching, Image Vision Comput. 19 (12) (2001) 821–832.
[15] M.A. Fischler, R.A. Elschlager, The representation and matching of pictorial structures, IEEE Trans. Comput. 22 (1973) 67–92.

[16] J.M. Fitzpatrick, J.B. West, A blinded evaluation and comparison of image registration methods, in: K.W. Bowyer, P.J. Phillips (Eds.), Empirical Evaluation Techniques in Computer Vision, IEEE Computer Society Press, Silver spring, 1998, pp. 12–27.
[17] J.C. Gee, M. Reivich, R. Bajcsy, Elastically deforming 3D atlas to match anatomical brain images, J. Comput. Assist. Tomo. 17 (2) (1993) 225–236.
[18] P. Gerlot, Y. Bizais, Image registration: a review and a strategy for medical applications, in: C.N. de Graaf, M.A. Viergever (Eds.), Information Processing in Medical Imaging, Plenum Press, New York, 1988, pp. 81–89.
[19] B. Julesz, Towards the automation of binocular depth perception, in: Proc. IFIP Congress 1962, North Holland, Amsterdam, 1963, pp. 439–443.
[20] J.A. Leese, G.S. Novak, B.B. Clark, An automatic technique for obtaining cloud motion from geosynchronous satellite data using cross correlation, A. Appl. Meteorol. 10 (1971) 110–132.
[21] H. Lester, S.R. Arridge, A survey of hierarchical non-linear medical image registration, Pattern Recognition 32 (1999) 129–149.
[22] M.D. Levine, D.A. O'Handley, G.M. Yagi, Computer determination of depth maps, Comput. Graph. Image Process. 2 (1973) 131–150.
[23] C. Lorenz, N. Krahnstöver, Generation of point-based 3-D statistical shape models for anatomical objects, Comput. Vision Image Und. 77 (2000) 175–191.
[24] K.E. Lunn, K.D. Paulsen, D.W. Roberts, F.E. Kennedy, A. Hartov, Nonrigid brain registration: synthesizing full volume deformation fields from model based solutions constrained by partial volume intraoperative data, Comput. Vision Image Und., this issue.
[25] J.B.A. Maintz, M.A. Viergever, A survey of medical image registration, Med. Image Anal. 2 (1) (1998) 1–36.
[26] C.R. Maurer Jr., J.M. Fitzpatrick, A review of medical image registration, Interact. Image-Guided Neurosurg. (1993) 17–44.
[27] K.I. Mori, M. Kidode, H. Asada, An iterative prediction and correction method for automatic stereocomparison, Comput. Graph. Image Process. 2 (1973) 393–401.
[28] R. Nevatia, Depth measurement by motion stereo, Comput. Graph. Image Process. 5 (1976) 203–214.
[29] S. Ourselin, A. Roche, G. Subsol, X. Pennec, N. Ayache, Reconstructing a 3-D structure from serial histological sections, Image Vision Comput. 19 (1/2) (2001) 25–31.
[30] N. Paragios, M. Rousson, V. Ramesh, Non-rigid registration using distance functions, Comput. Vision Image Und., this issue.
[31] W.K. Pratt, Correlation techniques for image registration, IEEE Trans. Aerospace Electron. Syst. 10 (3) (1974) 353–358.
[32] F.J.P. Richard, L.D. Cohen, A new image registration technique with free boundary constraints: application to mammography, Comput. Vision Image Und., this issue.
[33] L.G. Roberts, Machine perception of 3-D solids, Ph.D. Thesis, MIT, 1963.
[34] D.W. Roberts, A. Hartov, F.E. Kennedy, M.I. Miga, K.D. Paulsen, Intraoperative brain shift and deformation: a quantitative analysis of cortical displacement in 28 cases, Neurosurgery 43 (4) (1998) 749–760.
[35] L. Schad, S. Lott, F. Schmitt, V. Sturm, W.J. Lorenz, Correction of spatial distortion in MR imaging: a prerequisite for accurate stereotaxy, J. Comput. Assist. Tomo. 11 (3) (1987) 499–505.
[36] S. Sclaroff, J. Isidore, Active blobs: region-based, deformable appearances model, Comput. Vision Image Und., this issue.
[37] M. Singh, W. Frei, T. Shibata, G.C. Huth, A digital technique for accurate change detection in nuclear medical images with application to myocardial perfusion studies using Thallium-201, IEEE Trans. Nucl. Sci. 26 (1979) 565–575.
[38] P.A. van den Elsen, E.-J.D. Pol, M.A. Viergever, Medical image matching—a review with classification, IEEE Eng. Med. Biol. (1993) 26–39.
[39] A. Venot, V. Leclerc, Automated correlation of patient motion and gray values prior to subtraction in digitized angiography, IEEE Trans. Med. Imaging 8 (3) (1984) 179–186.
[40] Y. Wang, B.S. Peterson, L.H. Staib, 3-D brain surface matching based on geodesics and local geometry, Comput. Vision Image Und., this issue.
[41] A. Witkin, D. Terzopoulos, M. Kass, Signal matching through scale space, Int. J. Comput. Vision 1 (2) (1987) 133–144.