k-Tree Method for High-Speed Spatial Normalization

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Abstract: The general approach to spatial normalization using a deformation field is presented. Current high degree-of-freedom deformation methods are extremely time-consuming (10–40 hr), and a k-tree method is proposed to greatly reduce this time. A general k-tree method for analysis of source and target images and synthesis of deformation fields is described. The k-tree method simplifies scale control and feature extraction and matching, making it highly efficient. A two-dimensional (2-D), or quadtree, application program was developed for preliminary testing. The k-tree method was evaluated with 2-D images to test rotating ability, nonhomologous region matching, inner and outer brain-structure independence, and feasibility with human brain images. The results of these tests indicate that a three-dimensional (3-D), or octree, method is feasible. Preliminary work with an octree application program indicates that a processing time of under 10 min for 256^3 image arrays is attainable on a Sun Ultra30 workstation. *Hum. Brain Mapping* 6:358–363, 1998. © 1998 Wiley-Liss, Inc.

Key words: k-tree; quadtree; octree; spatial normalization

INTRODUCTION

Spatial normalization refers to the class of image processing algorithms that transform a source image to match homologous spatial features of a target image. In the human brain the goal is to reduce inherent spatial variability by matching corresponding anatomical features regionally down to the smallest structures resolved. Spatial normalization is accomplished using a common brain atlas image as the target. Numerous methods have been reported for brain spatial normalization, ranging in complexity from nine-parameter global affine transformations [Fox et al., 1985; Friston et al., 1991; Lancaster et al., 1995] to high degree-of-freedom warping

methods [Collins et al., 1994; Friston et al., 1995]. The high degree-of-freedom methods seek to resolve local as well as global anatomical differences between brains. It is common for the high degree-of-freedom methods to use a large deformation field to perform the spatial normalization. For three-dimensional (3-D) images, a deformation field is a three-dimensional array indexed by location, with each element being a three-component vector pointing from locations in the target brain to corresponding locations in the source brain. The length of the vector is usually recorded in millimeters, and one vector is provided for each voxel within the brain. The methods of Collins et al. 1994 and Friston et al. 1995 describe the complex nature of the image processing needed to synthesize large spatial deformation fields. In high-resolution MR images of the brain, image arrays are often 256^3 , requiring large deformation fields (3×128^3 array of floating point data). These can require long processing times ranging from 10–40 hr per brain volume [Collins et al., 1994].

Contract grant sponsor: NIMH; Contract grant sponsor: NIDA; Contract grant number: P20 MH/DA52176.

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Received for publication 2 April 1998; accepted 30 June 1998

BACKGROUND

Previously reported methods for decomposition of 3-D brain space and synthesis of high degree-of-freedom deformation fields were hierarchical and multiresolution in nature [Collins et al., 1994; Friston et al., 1995]. “Multiresolution” refers to the analysis of source and target image features with different levels of detail. The order of processing for multiresolution analysis methods is such that low-resolution images (low-pass-filtered to remove small and retain large structure features) are analyzed first. The analysis is repeated successively as the resolution is increased (amount of low-pass filtering reduced) to the highest possible image resolution (no low-pass filtering). The deformations needed to match features are calculated at the first hierarchical level and refined successively at each level until the synthesis is complete. This scheme is well-described by Collins et al. 1995. The general steps for calculating a deformation field using the hierarchical, multiresolution approach are:

- **Scale control.** Scale control is the general mechanism for the control of processing in paired regions of source and target brains. Processing moves from larger (low-resolution) to smaller (high-resolution) regions in accordance with a scale-change rule.
- **Feature extraction.** A set of parameters that measure significant spatial characteristics of paired regions within source and target brain image volumes is extracted.
- **Feature matching.** A deformation that spatially matches the extracted features of each paired region in the source and target brain image volumes is determined.
- **Continuity control.** Continuity constraints are used during the development of the deformation field to ensure a one-to-one correspondence between target and source image locations and that the deformation field is invertable.
- **Value control.** Depending on the nature of the image, correction in image values following spatial deformation may be required.

The basic processing steps are performed using a coarse-to-fine, global-to-local scheme that is iterated successively as the scale is reduced (Fig. 1). The deformation field is refined at each scale and used to transform the source image for comparison with the target image at the next scale.

OBJECTIVES

The objective of spatial normalization with k-trees is to develop a high-speed method for synthesizing

Figure 1.

General approach to spatial normalization using a deformation field. The deformation field is initialized to zero, the transformed and target images are analyzed, and the deformation is updated.

spatial deformation fields while maintaining the accuracy of high degree-of-freedom spatial normalization methods. To achieve this goal, efficient algorithms were selected that reduce both the number and complexity of calculations at each basic processing step. Scale control is usually achieved by removing high-frequency spatial information (small features) with low-pass filters [Collins et al., 1994]. Low-pass-filtered images are then sampled at a rate corresponding to their bandwidth. This processing is very demanding and computationally complex. It is well-known that decomposition and synthesis of multidimensional data is very efficient when k-trees are used [Meagher, 1980]. The k-tree approach for *scale control* is more efficient, since low-pass filtering is not required. Additional efficiency is obtained from the scheme used with the k-tree algorithm to divide an n-dimensional image into $k = 2^n$ regions. This subdivision progresses from the full image down to the smallest region that can be divided in a recursive manner. The scale-change rule is systematic (divide each region into 2^n equal-sized subregions) and predetermined (always creating the same regions) for a given array size. Feature parameters are extracted to match the scale and location of paired k-tree regions. The spatial centroid of each region is used for *feature extraction* since it is computationally simple, yet has significant positional information. For *feature matching*, paired feature parameters are analyzed to calculate a deformation that matches their spatial characteristics. The deformation for the k-tree method is calculated as the x, y, and z distances (i.e., vector components) between centroids of corresponding regions in source and target brains. *Continuity control* of the deformation field insures that shearing, tearing, overlapping, or gaps do not occur in the

transformed brain image. This may be done by algorithmic design [Collins et al., 1994; Friston et al., 1995] or by constraints applied during the calculation and refinement of the deformation field. For the k-tree method, modifying the deformation field near adjacent k-tree regions if a discontinuity is detected performs continuity correction. Discontinuity is indicated when the absolute value of the deformation field between adjacent pixels in the deformation field changes by more than one pixel. If detected, the deformations for bounding pixels are set equal to the average between regions. Deformations toward the interior of a region are incremented or decremented (whichever is necessary) until discontinuity is no longer present. This processing is only needed near boundaries of adjacent k-tree regions (Fig. 2), and tends to diminish with smaller and smaller regions. Currently, no *value control* is incorporated into the processing algorithms. The algorithms chosen for each processing step were selected to provide high efficiency and speed for spatial normalization, using a deformation field. One goal is to fully process a 256^3 image volume in less than 10 min. This research seeks to evaluate the speed, efficiency, and accuracy of the proposed k-tree spatial normalization method. This preliminary report focuses on speed and efficiency, with some simple measures of accuracy. Extensive accuracy measures are being tested for use with a proposed 3-D method.

MATERIALS AND METHODS

Basic scheme

While k-tree decomposition provides an efficient means to organize 3-D images, special processing methods are required for feature extraction, feature matching, and deformation field calculation/continuity management to take advantage of this efficiency. To simplify design and coding, a 2-D k-tree, or quadtree, spatial normalization (QSN) software application was written to study and optimize k-tree processing strategies for 3-D. QSN processing begins by shifting the geometrical mean location of a source image to match that of a target image. The image is then subdivided into equal quadrants (Fig. 2). Paired quadrants from source and target images are analyzed to determine their mean values. The geometric centroid of each quadrant is calculated using voxels with values greater than the mean value. This serves to isolate large regions within each quadrant while ignoring the effects of small regions above and below the threshold. The shift (or deformation) needed to translate the source quadrant to match the centroid of the paired

Figure 2.

A two-dimensional, or quadtree, subdivision of source and target images. Note how the transformed image can have discontinuities near quadrant boundaries that must be corrected.

target quadrant is then calculated. The shifts for each image quadrant are stored in corresponding quadrants of the deformation field. Continuity correction is performed near quadrant boundaries in the deformation field as needed. The deformation field is then used to transform the source image at full image resolution. This processing is repeated on the transformed data by successive subdivision of each quadrant into equal subquadrants until the entire image has been processed at a resolution of 2×2 pixels.

Rotation

The first test of the k-tree method was to determine whether centroid shifting could perform the equivalent of 2-D rotation for a simple object. This was evaluated by selecting a long rectangular region rotated 30° about the horizontal as the source and a similar, horizontally oriented rectangular region as the target (Fig. 3). For this test the length, position, and orientation of the source and target images were all different. The data were created in 32×32 arrays using rectangular regions of interest, and the regions were filled with a value of 100.

Several measurements were made to test if the rotated rectangle was spatially distorted. First, a global distortion test was done using sites along the trans-

Figure 3.

The k-tree transformation of an angled 2-D source rectangle to a horizontally oriented target rectangle.

formed rectangle at 0%, 33%, 50%, 67%, and 100% of its length. These sites were inverse-transformed to the source rectangle and similar fractions of length calculated for comparison. Second, an estimate of local distortion was performed by comparing the calculated spacing between assumed equally-spaced sites in the source rectangle with the predicted spacing of 1.17 pixels (determined using ratio of measured lengths of rectangles). The source site locations were calculated by inverse transformation of equally-spaced pixel sites along the transformed rectangle. The alignment of the transformed rectangle to the x-axis simplified the selection of equally-spaced pixel locations, and all 18 pixels along its long axis (Fig. 3) were used. Local positional distortion was estimated as the difference between measured and predicted spacing for the 18 successive sites along the source rectangle.

Nonhomology

The second test of the k-tree method was to record its performance when source and target images were nonhomologous. To do this, we made a circular source image and an elongated and enlarged target image with a protrusion along its upper right margin (Fig. 4). Test images were recorded in 32×32 arrays, and the interiors of both source and target images were filled with a value of 100.

Simulated brain

The third test was to determine if the k-tree method could transform inner brain regions independently of outer brain regions. Inner (corpus callosum) and outer (brain surface) regions were manually outlined on a midsagittal MR brain image. The regions were transferred to a 64×64 array for processing. The outer region was assigned a value of 50 and the inner region a value of 100. Source and target images were different in shape, size, and orientation for both inner and outer brain regions. For this processing there were five levels of quadtree subdivision, ranging from 4 quadrants of 32×32 pixels to 1,024 quadrants of 2×2 pixels (Fig. 5). A mean square error (MSE) between transformed and target images was calculated at each processing level to measure their difference and assess the improvement of fit at successive levels. The processing was performed with a weighted centroid method, and with a mean-value threshold centroid method for comparison.

Human brain

Midsagittal slices from T1-weighted MR images in 2 normal subjects were evaluated to test feasibility of the k-tree method with real brain images. Images were converted to 64×64 arrays for processing. Images were edited to remove nonbrain tissues. The brain stem was removed below the level of the cerebellum to

Figure 4.

The k-tree transform of a 2-D image where the source and target were nonhomologous along their upper right boundary.

Figure 5.

Level-by-level k-tree transform of simulated 2-D brain images, with source and target images having different inner and outer brain regions.

insure that the inferior margin of the cerebellum defined the inferior margin of the brain.

RESULTS AND DISCUSSION

Rotation

Figure 3 shows that the k-tree method can effectively rotate a simple 2-D object to match a similarly shaped object (rectangle). The transformed image shows the effects of aliasing [Foley et al., 1990] that were present in the rotated source rectangle. Values in the transformed image were calculated using bilinear interpolation, which also smooths around boundaries. To provide a comparable visual image, the transformed image in Figure 3 was thresholded to show only points above 50% of the maximum value.

For the global distortion test, all sites fell within 0.6% (0.126 pixels) of their predicted locations. The regional distortion test yielded adjacent site distance errors of 0.09 ± 0.19 pixels. The maximum and minimum errors were 0.44 and -0.18 pixels. These data suggest that the k-tree method can effectively rotate a simple rectangle with little added distortion. The orientation difference that can be accommodated by the k-tree method was not evaluated. For most objects it is advisable that global orientation differences be reduced prior to processing.

Nonhomology

Figure 4 shows the performance of the k-tree method for the nonhomology between source and target im-

ages introduced locally in the target image. The boundary of the transformed image falls between that of the source and the target for the nonhomologous region. However, transformed and target images matched well along the remainder of the boundary, though the transformed image is smoother. A similar result was obtained (not shown) when the source and target images were swapped. The fabrication of a feature in a transformed image when none exists in the source image is of great concern, and the compromise provided by the k-tree-fitting algorithm seems reasonable. This will need to be tested in much greater detail with real brain data as the 3-D method is developed and optimized.

Simulated brain

Figure 5 shows the effect of k-tree spatial normalization at each level of processing for the 64×64 simulated brain images. The 64×64 array was a limit imposed by the memory on the computer system where the 2-D feasibility testing was done. The weighted centroid method did not perform as well as the mean-value threshold centroid method. This is believed to be due to the fact that the threshold method better isolated individual structures in multivalued data prior to centroid calculations. The threshold centroid method results are given in Figure 5.

The final level of processing (level 6) shows that rotation, translation, and scaling were successful for both inner and outer brain regions. The mean square error (MSE) of the difference between the transformed and target image as a function of level is plotted in Figure 5.

The MSE is reduced at each successive level of processing, with the smallest error seen for the full deformation (11% of initial MSE). A small residual is expected in the MSE due to the bilinear interpolation used for transforming the source, though its magnitude was not measured. To eliminate accumulated interpolation effects, intermediate transformed images are calculated from the source data, ensuring that interpolation is never performed more than once. This experiment indicates that inner and outer regions of the brain were calculated independently. This experiment also confirms that the continuity correction method is adequate for such data.

Human brain

Figure 6 shows the results of transforming a source brain image to a target brain image and vice versa. Several findings are apparent from these images. First,

Figure 6.

Forward and reverse k-tree transform of 2-D source and target brain images (64×64 arrays).

the outer brain margins, where contrast is high, appear to match well in shape, dimension, and orientation. Second, inner structures, where contrast is low, match with varying levels of success. The success of this match appears to be related to signal level. The corpus callosum (high signal level) transforms reasonably well from the source to the target. The reverse transform appears good, but contrast is too poor to confirm this. The low-signal area between the cerebellum and the cerebrum did not match well for either the forward or reverse transform. The successes and failures of this feasibility test will be used to guide the development of the 3-D or octree version of spatial normalization.

The processing time for the 64×64 image was 4 sec on a 90-MHz Pentium PC. This translates to approximately 5 hr for a 256^3 image. This time is much less than the reported time of 10–40 hr [Collins et al., 1995] using a high-performance Silicon Graphics, Inc. computer. The QSN software was written in the “visual basic for applications” (VBA) environment provided with Microsoft Excel 5.0. VBA is not optimal for speed, but was helpful for this feasibility study because of the ease with which results could be stored and analyzed in associated Excel spreadsheets.

CONCLUSIONS

The findings of this feasibility study suggest that the k-tree method for transforming a source image to a

target image using a high degree-of-freedom deformation field can be accomplished at a higher speed, and with similar accuracy, when compared with current methods.

Based on this feasibility study, an octree method is under development for use with 3-D T1-weighted MR images at their full resolution. A compatible standard template for spatial normalization exists, developed for use with the ICBM project [Mazziotta, et al 1995], and can be used for spatial normalization. Additionally, the 3-D deformation fields will be tested with lower-resolution PET, SPECT, and fMRI images, coregistered to source MR images, to determine effectiveness of spatial normalization across modality. Preliminary testing of a 3-D version of octree spatial normalization indicates that a total processing time of less than 10 min for 256^3 arrays is achievable on a Sun Ultra30 workstation. Several areas will be investigated in greater detail with the 3-D software, including improved feature matching, management of incomplete image volumes, and refinement of the continuity correction algorithm.

ACKNOWLEDGMENTS

Research support was provided by the Human Brain Project, funded by the NIMH and by NIDA (P20 MH/DA52176).

REFERENCES

- Collins DL, Neelin P, Peters TM, Evans AC (1994): Automatic 3D intersubject registration of MR volumetric data in standardized space. *J Comput Assist Tomogr* 18:192–205.
- Collins DL, Holmes CJ, Peters TM, Evans AC (1995): Automatic 3-D model-based neuroanatomical segmentation. *Hum Brain Mapp* 3:190–208.
- Foley JD, van Dam A, Feiner SK, Hughes JF (1990): *Computer Graphics: Principles and Practice*, 2nd ed. Reading, MA: Addison-Wesley.
- Fox PT, Perlmuter JS, Raichle ME (1985): A stereotactic method of anatomical localization for positron emission tomography. *J Comput Assist Tomogr* 9:141–153.
- Friston KJ, Frith CD, Liddle PF, Frackowiak RSJ (1991): Comparing functional (PET) images: The assessment of significant change. *J Cereb Blood Flow Metab* 11:690–699.
- Friston KJ, Ashburner J, Frith CD, Poline JB, Heather JD, Frackowiak RSJ (1995): Spatial registration and normalization of images. *Hum Brain Mapp* 3:165–189.
- Lancaster JL, Glass TG, Lankipalli BR, Downs H, Mayberg H, Fox PT (1995): A modality-independent approach to spatial normalization of tomographic images of the human brain. *Hum Brain Mapp* 3:209–223.
- Mazziotta JC, Toga AW, Evans A, Lancaster JL, Fox PT (1995): A probabilistic atlas of the human brain: Theory and rationale for its development. *Neuroimage* 2:89–101.