Multilevel 3D Registration of Lung Surfaces in Computed Tomography Scans – Preliminary Experience*

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ABSTRACT

We developed an efficient multilevel method for surface registration in medical images. The multilevel method is applied to two sets of three-dimensional points that model the two surfaces to be aligned. The multilevel method first reduces the original number of points and aligns them using an iterative surface registration method. The optimal solution for aligning the coarse surface models is then applied to match finer surface models. This process is repeated until the surfaces are registered at their original resolution. Our surface registration method can be understood as an extension to the "Iterative Closest Point" (ICP) algorithm [2, 8]. It uses a nearest neighbor search method that improves the efficiency of the original ICP algorithm. We match midpoints between the closest and second closest points to establish correspondences of surface points. We also compute an initial alignment of the surfaces using point-to-point registration of landmarks. We present results for aligning the lung surfaces segmented from the computed tomography scans of seven patients with and without the multilevel approach and demonstrate that the multilevel approach is superior in efficiency and accuracy.

Keywords: Multilevel Methods, Surface Registration, Chest CT

1. Introduction

The multilevel method is considered one of the most effective techniques for solving numerical, combinatorial, and geometric problems. A systematic introduction of the fundamental elements of the multilevel method is given by Teng [7]. The multilevel method has been used in a wide array of problems: domain decomposition, geometric search structures, multigrid, partitioning, and sparse matrix ordering.

Computer vision applications of the multilevel method often use an "image pyramid" that contains representations of the image at different resolution levels [1]. A problem, such as object recognition, object detection, or image compression, is first solved for the image with lowest resolution. The solution is projected to the next level, where it is used to solve the problem for the image with the second lowest

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resolution and so forth. The process repeats until the problem is solved for the original, highest resolution image.

In medical image processing, the following two approaches in the literature are most closely related to our work. Feldmar et al. [4] describe a coarse-to-fine approach for intensity-based registration of three-dimensional (3D) brain volumes that extends the iterative closest point (ICP) method [2, 8]. Metaxas et al. [6] use a multilevel approach to compute a triangulation of a lung surface. At each level, transformations are applied to improve the surface model, and the number of triangles that make up the model is divided by two.

We developed a multilevel method for registering lung surfaces that uses a coarse-to-fine approach, similar to the above methods. In our approach, the surface is modeled by a set of 3D-point sets that are organized in connected contours. The contours were segmented from computed tomography (CT) scans as described in Ko et al. [5]. Two surfaces were segmented from two scans of each patient taken at different times. For each surface, a hierarchical set of surface models is built from the finest at the top level to the coarsest at the lowest level. At each level of the hierarchy of surface models, an iterative registration algorithm is applied that is based on the ICP method. The coarsest surface models are first aligned and the solution is applied to match the finer models of the surfaces at the next level.

To improve the speed of the original ICP algorithm, we use an efficient neighborhood search algorithm for establishing point correspondences and compute an initial alignment of the surfaces using point-to-point registration of chest landmarks [3].

We introduce a new approach to establish correspondences. Instead of using the point with the smallest Euclidean distance to define correspondence, as in the original ICP method, we use the midpoint between the two closest points. Since the midpoint may be a better approximation of the true position of the corresponding point than the closest point, this strategy can result in a better surface alignment at lower levels.

2. Multilevel Method

The multilevel method is a class of methods for solving computation and optimization problems [7]. The multilevel method is based on three key steps: coarsening, projection, and smoothing. For coarsening, we define a hierarchical set of problems $P = P_0, P_1, \ldots, P_L$, where P_i is a coarser approximation of P_{i-1} and $1 \leq i \leq L$. Building a coarsening hierarchy usually involves resolution reduction, for example to create image pyramids, or sampling.

The solution S_i of P_i and S_{i-1} of P_{i-1} are closely related. It may be easier or more efficient to solve P_i than P_{i-1} since P_i is a coarser approximation of P_{i-1}. For projection, the strategy is therefore to solve the easiest problem P_L first and then use the solution S_L of P_L to produce an initial solution of P_{L-1}. For smoothing, we construct the solution S_i starting with the projected solution as an initial estimate. We continue to project and smooth at each level until the original problem P_0 is solved.

Basic Multilevel Scheme (P_0, L)
1. Bottom-Up Phase: for $i = 1$ to L
   P_i = coarsen (P_{i-1})
2. Basis Step: find a solution S_L of P_L
3. Top-Down Phase: for $i = L$ to 1 with step -1
   $S_{i-1} = \text{smooth}_{P_{i-1}}(\text{project } (S_i))$

3. Multilevel Surface Registration

We present a multilevel approach to lung surface registration. We begin with P_0, which represents the problem of registering the two lung surfaces at their original resolution. The same problem is represented by $P_1, \ldots, P_L$, only with a reduced number of surface points. For example, P_0 contains the original number of surface points and P_1 has $k\%$ of the points in P_0, where k is a sampling factor, and so forth. The basic strategy is to find the solution S_L for P_L first and then, level by level, construct S_{i-1} from the solution S_i for each i.

Most of the processing time of our registration method is spent on finding the correspondences of lung surface points. The multilevel method allows us to perform the registration process by reducing the number of points without sacrificing overall accuracy.

We start with the base case by performing the iterative registration process on P_L, which has the smallest number of points. After a number of iterations, we then project the solution S_i, which is a set of transformation parameters, up one level to P_{i-1} and apply it to obtain an initial alignment on the lung surfaces in P_{i-1}. In the smoothing step, S_{i-1} is computed by performing the iterative registration process on the transformed points in P_{i-1}. We continue to project the solution and smooth until the original problem P_0 is solved.

4. Iterative Registration Algorithm

At each level in our multilevel registration approach, we apply an iterative registration method similar to the iterative closest point scheme [2, 8]. At each iteration, we apply a rigid-body transformation to align the two surfaces. The original ICP algorithm uses the measure of the smallest Euclidean distance to define correspondence. We modified step 1 in order to allow the use of another measure: the midpoint between the point with the closest and second closest Euclidean distance.

4.1. Nearest Neighbor Search

An exhaustive search for establishing point correspondences has a time complexity that is quadratic in the number of surface points, since the Euclidean distance between each point pair must be computed. To efficiently establish correspondences, we use the neighborhood search algorithm. The algorithm finds closest points by searching in the local neighborhoods of the surface points. The algorithm takes as input the points on surface 2 and the points on surface 1 that are transformed into the coordinate system of surface 2 for alignment.

1. For each point p on surface 2, check if its adjacent voxels contain transformed surface points.
2. If such points exist, select among them the point x with the smallest Euclidean distance to p. Otherwise expand the search space by one voxel in all directions.
3. Repeat the search process until the closest transformed point x is found.

Our neighborhood search algorithm generally only processes a linear number of voxels that surround the surfaces, unless the surfaces are significantly misaligned. It is therefore substantially more efficient than the brute-force exhaustive search algorithm.

4.2. Landmark Detection and Registration for Initial Alignment

The iterative registration algorithm may not converge to the desired solution, if the two surfaces are initially severely misaligned. We therefore compute an initial alignment of the lung surfaces. This strategy may avoid local minima and significantly reduce the overall processing time.

We use landmark detection and point-to-point registration of chest landmarks to achieve the initial alignment of the lung surfaces [3]. Template images of cross-sections of anatomical landmarks, such as sternum, vertebra, and trachea, are used to detect the landmarks in our original CT data. The templates are correlated with the original CT data to estimate the position of the landmarks. The normalized correlation coefficient is used to evaluate the template match.

Given the positions of four landmarks in each of the two scans, the rigid-body transformation is computed that optimally aligns the corresponding landmarks in the two scans. The transformation parameters are then applied to the lung surfaces to compute an initial alignment.

5. Results and Discussion

Our data consist of lung surfaces segmented from two CT scans of seven patients. The scans have a resolution of 512×512 voxels per slice and a slice thickness of 10/5/10 mm, 5 mm, or 1.25 mm. The 10/5/10 mm CT scans were obtained from the lung apices through the adrenal glands with 10 mm collimation and 5 mm collimation through the hila. The number of points on the lung surfaces is about 50,000 – 75,000 for 10/5/10 mm data and 500,000 – 750,000 for 1.25 mm data. Our surface registration results are summarized in Table 1 for the closest-point approach.

To find the version of the multilevel method that achieves the best experimental results for the lung surface registration problem, we tested three strategies.

Uniform sampling. To coarsen the set of points at each level, we uniformly sampled 50% of the points on each surface contour. Level P_0 contains the original number of points, P_1 contains half the points in P_0, P_2 a quarter of the points in P_0, P_3 an eighth of the points in P_0 and so forth (see Fig.1). At each level, the iterative

Table 1: Registration Results

RMS (root mean squared) error between corresponding surface points based on multilevel registration with landmark-based initial alignment (MRL), multilevel registration without landmark-based initial alignment (MR), registration with landmark-based initial alignment (RL), and registration without landmark-based initial alignment (R).

Patient	Slice Thickness (in mm)	RMS Error (in mm) MRL and MR	RL	R
1	10/5/10	5.4	5.4	6.2
2	10/5/10	3.5	3.6	4.7
3	5	3.8	4.1	4.4
4	5	4.2	4.5	5.3
5	5	3.8	4.1	3.8
6	1.25	4.3	4.3	4.4
7	1.25	2.2	2.2	2.2
Average		3.8	4.0	4.4

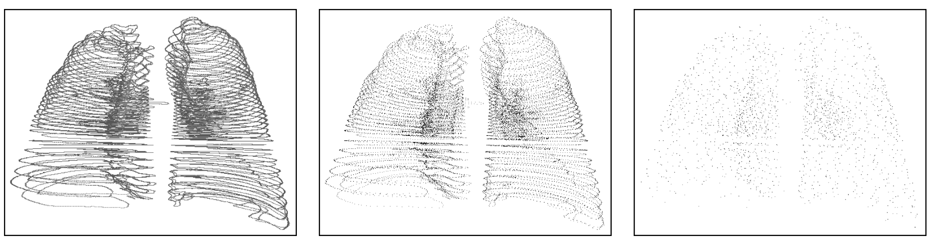

Figure 1. Lung surfaces of patient 1 for levels 0, 3, and 6.

registration process continues until the threshold of one percent change in error is reached.

Our experiments with changing the number of coarsening levels indicate that the most accurate results are obtained if the lung surfaces are coarsened to about 608 points. This means that on average 8 coarsening levels are used for 10/5/10 mm data and about 10 levels for the 1.25 mm data.

Midpoint Approach. The midpoint approach increases the accuracy by 1.2% for initially aligned surfaces and 2.4% for non-aligned surfaces compared to the original closest-point approach. However, there is a tradeoff between accuracy and efficiency, because additional processing time is needed to find the second closest point and compute the midpoint. The efficiency of the midpoint method depends on the degree of alignment. If the surfaces are initially aligned, the midpoint approach increases the average running time by 22.4% compared to the original closest-point approach. For the non-aligned case, the running time only increased by 1.0%.

Initial Landmark-based Alignment. The multilevel closest-point approach that uses initial alignment is as accurate as the approach without initial alignment.

It results in an average improvement of 7.1% in efficiency. If both processing times of landmark detection and surface registration are considered, the non-aligned registration approach is twice as fast, thus making the landmark-based alignment seem unnecessary. On our 1 GHz Pentium processor with 1 GB of RAM, the average registration time for the multilevel approach after initial alignment is 102 s.

6. Conclusions

We introduced a multilevel approach to surface registration and applied it to the problem of aligning lung surfaces. Our experiments show that accuracy and speed of the iterative registration process is improved by incorporating the multilevel approach. In the future, we plan to include our implementation in a diagnostic imaging system that assists radiologists in evaluating and comparing sequential chest CT scans.

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