Registering 3D Lung Surfaces Using the Shape Context Approach*

Martin Urschler and Horst Bischof†

Institute for Computer Graphics and Vision, Graz University of Technology

Abstract. Studying the complex thorax breathing motion is an important research topic for medical (e.g. fusion of function and anatomy, radiotherapy planning) and engineering (reduction of motion artifacts) questions. In this paper we present first results on studying the 4D motion of segmented lung surfaces from CT scans at several different breathing states. For this registration task we extend the shape context approach for shape matching by Belongie et al. [1] from 2D shapes to 3D surfaces and apply it to segmented lung surfaces. Resulting point correspondences are used for a non-rigid thin-plate-spline registration. We describe our experiments on synthetic and real thorax data and show our quantitative and qualitative results.

1 Introduction

According to the European Respiratory Society, lung diseases rank second behind cardiac diseases in terms of mortality and cost of treatment. Computerized methods for objective, accurate and reproducible analysis of lung structure and function can provide important insights into these problems. However, due to the complexity of the breathing motion, investigations are often very complicated. In this paper we present first results on studying the 4D motion of segmented lung surfaces from several different breathing states scanned between Functional Residual Capacity (FRC) and Total Lung Capacity (TLC). We especially regard the problem of matching surfaces from consecutive breathing states and non-rigidly registering them by using a thin-plate-spline transformation model [2] for the deformation of the corresponding points. In general it is not possible to robustly derive corresponding features from the lung surfaces since the diaphragm-induced motion component and the movement of the rib cage tend to deform the elastic lung tissue, such that e.g. ridges might become valleys after deformation. The shape context approach introduced by Belongie et al. [1] was reported as a reasonable and promising method for matching 2D shapes (especially hand-written digits and letters) and 2D object recognition without relying on extracted features. We extend this approach to match 3D shapes and we are up to our knowledge the first ones to apply it to 4D medical image data, i.e. the segmented lung surfaces at several breathing states. Our image data stems from high-speed multi-detector spiral CT sheep studies. The sheep CT data was provided by Prof. Eric Hoffman, University of Iowa. The data is acquired at several (two, four or five) breathing states between TLC and FRC by a protocol where breath is held at fixed inspiration levels during the 30 sec scan time. This leads to a static breathing scheme, which has to be considered for the interpretation of derived motion models from matched and registered shapes. However, a protocol to scan thorax anatomy at different breathing states with high spatial resolution during dynamic (normal) breathing is currently not feasible. The image dimensions per breathing state are 512x512x550 with voxel dimensions of 0.52mm x 0.52mm x 0.6mm.

2 Method

2.1 Related Work

An older survey on the state of the art in 2D shape matching can be found in Veltkamp et al. [3]. Audette et al. give an algorithmic overview of surface registration techniques for medical imaging in [4], while Zitova et al. recently published an overview of image registration techniques [5]. Some examples for closely related methods for shape matching/registration are the modal matching approach proposed by Sclaroff et al. [6] or the TPS-RPM (Thin-Plate-Spline - Robust Point Matching) method developed by Chui et al. [7]. The main contribution of the work from Belongie et al. [1] is to present a robust and simple algorithm for finding shape correspondences by using shape context as a very discriminative representation that incorporates global shape information into a local descriptor.

2.2 The Shape Context Approach

The shape context approach [1] treats objects as (possibly infinite) point sets and assumes that the shape of an object is captured by a finite subset of its points, giving us a set $P = \{p_1, ..., p_n\}$. The points can be obtained as

* We gratefully acknowledge the support of Prof. Eric Hoffman, Department of Physiologic Imaging, University of Iowa, Iowa City for providing the CT image data.

† EMail: {urschler,bischof}@icg.tu-graz.ac.at

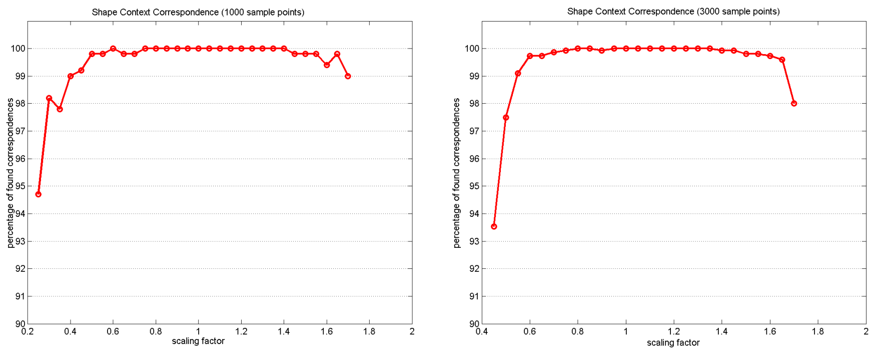

Figure 1. Percentage of found correspondences with the shape context approach. A series of scaling transformations was applied to a lung surface. Left plot shows results with 1000 sampled points, right image shows results with 3000 sampled points.

locations of edges from an edge detector or from another method to sample contour/surface points from a shape. The points need not and typically will not correspond to key points or structures such as maxima of curvature, inflection points or surface ridges. In contrast to the original implementation we lay strong emphasis on the discretization method. We are using a marching-cubes polygonization and sample contour points regularly from the constructed mesh. For each point p_i on the first shape, the "best" matching point q_i on the second shape has to be located. Therefore, the shape context descriptor is introduced. If we look at the set of vectors emitted from one point to all others, we can interpret this set as a rich description of the shape configuration relative to that point. Since this description is much too detailed, we take the distribution of the set of vectors as a compact, yet highly discriminative descriptor instead. So for each point p_i a histogram h_i of the relative position of the remaining points is calculated which is called the *shape context*. Now for point p_i from the first shape and q_j from the second shape, let $C_{ij} = C(p_i, q_j) = \frac{1}{2}\sum_{k=1}^{K}\frac{[h_i(k)-h_j(k)]^2}{h_i(k)+h_j(k)}$ denote the cost of matching these two points. Given the set of costs C_{ij} between all pairs of points on the first and second shape, we want to minimize the total cost of this one-to-one matching problem, which is an instance of the weighted bipartite matching problem. It can be solved in $O(N*(M+N*logN))$ time, with N being the number of nodes and M the number of edges in the graph. Here the original matching algorithm has been replaced by a more efficient one since the 3D case requires many more sample points than the 2D case which may lead to high run-times of the algorithm. The result of this step is a one-to-one mapping of corresponding points from the two shapes.

2.3 Non-Rigid Registration

After establishing the point correspondences we make use of the thin-plate-spline framework [2] due to its reported well suited applicability for modeling changes in biological forms. The thin-plate-spline approach leads to a transformation that consists of an affine part and a non-linear deformation part. The parameters of the thin-plate-spline model are calculated from the constraint that corresponding points are exactly interpolated and that the spline model between corresponding points is regular and smooth.

3 Results

To assess the validity of the shape context approach we performed quantitative evaluations on synthetic data sets. Further we used real thorax data for qualitative and quantitative evaluations. For our first synthetic study we took a single segmented lung surface and applied a series of known rigid scaling transformations to it. Afterwards we applied the shape context approach on the original and each transformed data set and calculated the percentage of correctly found corresponding points. The results for two distinct cases (sampling 1000 and 3000 points from original and transformed lung surface respectively) are depicted in Fig. 1.

Our second synthetic study uses a series of known thin-plate-spline transformations to create pairs of lung surfaces for shape matching. Therefore, we took two data sets at distinct breathing states (TLC and FRC) from our segmented real thorax data. We applied the shape matching algorithm and performed a thin-plate-spline transformation to get a plausible transformation T. This transformation T was then used as known "gold-standard"

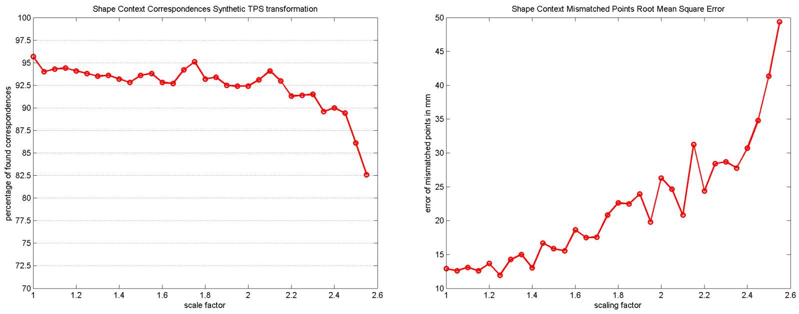

Figure 2. Matching results after applying a series of thin-plate-spline transformations with differing scales to a lung surface. Left plot shows percentage of found correspondences with the shape context approach on original and synthetically transformed data sets. Right plot shows the root mean square errors of the mismatched points compared to their original location. Surfaces were sampled with 1000 points.

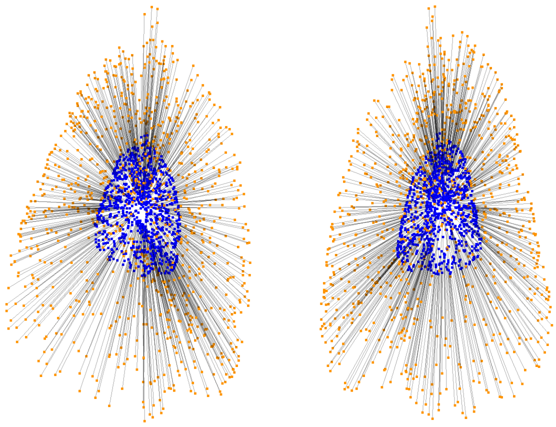

Figure 3. Two views of the matched points from the synthetically transformed (thin-plate-spline transformation) lung surfaces. The affine part of the thin-plate-spline transformation was a scaling transformation with scale factor 1.75.

transformation for our synthetic evaluation. We kept the non-linear part of T which resembles the deformations of the lung surface. Yet, the affine part of T was replaced by a series of scaling transformations with differing scale factors, giving a set of synthetic transformations $\{T_1, ..., T_n\}$. Then each of these transformations T_i was applied to the points of the lung surface at TLC. The TLC lung surface and the transformed lung surface were taken as input for the shape matching method and the resulting point correspondences were registered leading to transformations $\{T_1^{'}, ..., T_n^{'}\}$. So we could calculate a percentage of found correspondences and the root mean square error of distances between mismatched points and their original locations from comparing $T_i^{'}$ with T_i respectively. These results are depicted in Fig. 2. From the results of the second experiment we conclude that the performance of the shape context matching is very well in a wide range of scales, but decreases as soon as the scale factor gets too large. However, this is neglectable since too large scales resemble no meaningful simulation of breathing anymore. Two views of the matching result using a scale factor of 1.75 are shown in Fig. 3.

Finally we performed an evaluation using a data set with five different breathing states (TLC, FRC and three states inbetween). We built four subsets of these breathing states consisting of states $\{$1,2,3$\}$, states $\{$2,3,4$\}$, states $\{$3,4,5$\}$ and states $\{$1,3,5$\}$ respectively. The number of sample points was 1000 in all experiments. For each of these subsets we calculated the transformation $T^{'}$ relating first and second state and $T^{''}$ relating second and third states by using the shape context matching approach. Further we calculated $T^{'''}$ relating first and third state. Then we compared the results of applying $T^{'''}$ and applying $T^{''}(T^{'})$ on the first breathing state by calculating error statistics on the displacement of the transformed points. These results are given in Table 1. Screenshots of the results for a single pair of breathing states are shown in Fig. 4.

Data Subset	mean[mm]	std-dev[mm]	rms[mm]	min[mm]	max[mm]
{1,2,3}	5.81	4.61	7.42	0.14	24.24
{2,3,4}	5.97	4.39	7.41	0.29	25.57
{3,4,5}	6.18	3.87	7.29	0.21	22.10
{1,3,5}	6.14	4.17	7.42	0.12	35.02

Table 1. Results of the shape context validation on real data. For each subset mean, standard deviation, root mean square, minimim and maximum displacement of the transformed points was calculated.

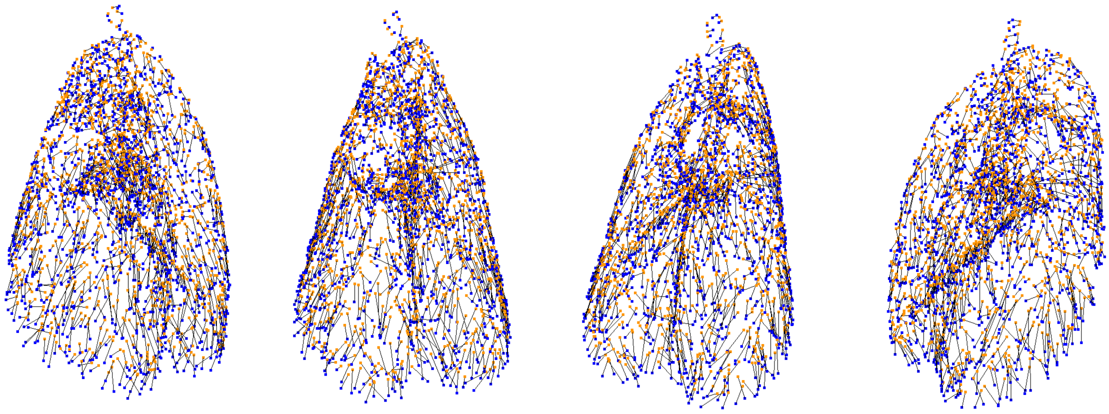

Figure 4. Four views of the matched points from an example pair of lung surfaces. 1000 sample points were used respectively for the shape context approach.

4 Discussion

We have demonstrated a 3D extension of the shape context approach for matching 3D lung surfaces. Shape context is a promising technique to find corresponding points for non-rigidly registering deformable anatomical structures which might also be useful for other 3D registration tasks in the medical domain. Our first experiments proved the validity on synthetic data and evaluated real-life data quantitatively and qualitatively. Future work will consist of more elaborate evaluations of the registration accuracy of our approach. In this context it will become possible to assess the semantic correctness of the found correspondences as well. Another intended task is a comparison of our approach with different state of the art matching techniques like the robust point matching approach proposed by Chui and Rangarajan [7]. Further topics will be to look into the elastic-body spline transformation proposed by Davis et al. [8] for registration instead of using the thin-plate-spline transformation and to investigate the robustness of this approach in case of noise and outliers.

References

1. S. Belongie, J. Malik & J. Puzicha. "Shape matching and object recognition using shape contexts." *IEEE Transactions on Pattern Analysis and Machine Intelligence* **24(4)**, pp. 509–522, 2002.
2. F. L. Bookstein. "Principal Warps: Thin-Plate Splines and the Decomposition of Deformations." *IEEE Transactions on Pattern Analysis and Machine Intelligence* **11(6)**, pp. 567–585, June 1989.
3. R. C. Veltkamp & M. Hagedoorn. "State of the Art in Shape Matching." Technical Report UU-CS-1999-27, Utrecht, 1999.
4. M. A. Audette, F. P. Ferrie & T. M. Peters. "An algorithmic overview of surface registration techniques for medical imaging." *Medical Image Analysis* **4**, pp. 201–217, 2000.
5. B. Zitova & J. Flusser. "Image registration methods: A survey." *Image and Vision Computing* **21(11)**, pp. 977–1000, October 2003.
6. S. Sclaroff & A. Pentland. "Modal Matching for Correspondence and Recognition." *IEEE Transactions on Pattern Analysis and Machine Intelligence* **17(6)**, pp. 545–561, June 1995.
7. H. Chui & A. Rangarajan. "A new point matching algorithm for non-rigid registration." *Journal of Computer Vision and Image Understanding* **89**, pp. 114–141, 2003.
8. M. H. Davis, A. Khotanzad, D. P. Flamig et al. "A Physics-Based Coordinate Transform for 3-D Image Matching." *IEEE Transactions on Medical Imaging* **16(3)**, pp. 317–328, June 1997.