Individualized Geometric Model from Unorganized 3-D Points: An Application to Thorax Modeling

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Abstract. An accurate surface model is necessary in many biomedical applications. An anatomical volume image, like MR volume image, is not always available. In this paper, we compare different, mainly previously published, registration methods that can be used to generate an individual geometric model when the only information on the patient is a set of digitized points from the surface of the skin. In addition, different aspects of the 3-D point selection are studied. The comparison is performed using 22 manually segmented thorax MR volume images.

1 Introduction

Detailed 3-D geometric models are needed in numerous scientific and industrial problems, such as in computer graphics and finite-element engineering problems. Also, in the biomedical field, a wide range of applications exists utilizing individualized geometric data. The most accurate way to build a geometric model is to segment the objects needed from anatomical volume data, such as MR or CT volume images. However, such an image is not always available, in which case some other information must be used, e.g. digitized surface points. This paper concentrates on techniques to reconstruct 3-D geometry from a digitized 3-D point set. Although a few methods have been published applicable to the problem, the comparison of the methods as well as the assessment of different aspects of the problem have not been carefully evaluated.

The geometric data used in this study are sparse and unorganized which makes the reconstruction of 3-D geometry difficult. The use of *a priori* geometric knowledge is often a pre-requisite for successful reconstruction. Approaches encountering the problem are not, however, numerous. Free-form deformations (FFD), allowing regularized 3-D spatial transformation for a geometric *a priori* model, have been proposed for the problem of sparse data sets [1,2]. In addition, methods utilizing information on typical deformations derived from a database have been applied to sparse data [3,4]. The use of physically based free-vibration modes have also been reported [5].

In this paper, the application area is the thorax. The presented methods can be applied e.g. to solving the inverse problems of electro- (ECG) or magnetocardiography (MCG) source localization studies, where individualized volume conductor models, which take into account the variations in the size and shape of the body, and the internal inhomogeneities, must be used to achieve accurate results [6]. However, the methods reported

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can be as well applied to other regions of interest, such as real-time tracking in image guided surgery [7].

The objective of the work described in this paper was to study how a surface point set should be selected to build a geometric thorax model, and what is the accuracy of different techniques to reconstruct the 3-D geometry. In the studied techniques, the common principle was to register an *a priori* surface model, consisting of the torso, left and right lung, and epicardium surfaces, to the points located from the torso surface, i.e., the reconstruction problem was treated as a registration problem. Affine and non-rigid registration approaches were tested in the 3-D reconstruction. In the non-rigid registration, both standard free-form deformation (FFD) grid as well as statistical deformation models (SDMs) were validated. In addition, different approaches to choose an *a priori* model were studied. A technique based on regression analysis was also proposed to correct the location and size of the internal organs, as the points were located only from the torso surface.

2 Material and Methods

2.1 Volume Image Database

The database used in this work consisted of the T1-weighted thorax MR volume images of 22 subjects (11 males and 11 females). The original size of the volumes was $256 \times 256 \times 40$ and the voxel size was about $2 \times 2 \times 10$ mm^3. These volumes were transformed into isotropic volumes: size $128 \times 128 \times 150$, voxel size about $3.9 \times 3.9 \times 3.9$ mm^3. The torso, both lungs, and epicardium were segmented from these volumes using a manual segmentation software, and triangle surface models were generated.

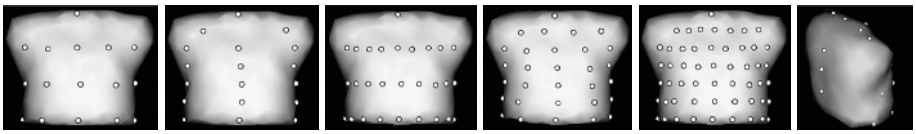
2.2 Set of Surface Points

The registration accuracy depends certainly on the number and position of the surface points. In practice, the number of the points should be kept as low as possible in order to reduce the workload of clinical staff in digitization. In this work, different sets of surface points were located from the torso surfaces in the MR volume images. In this way, we were able to define the registration error outside the surface points (target registration error) because the real geometry was available in the MR volume images.

In this study, five sets of surface points were compared (Fig. 1). Usually, when the digitization takes place, the patient is lying on his/her back in a bed. Therefore, no points can be digitized from the back. However, considering the registration accuracy, it is important to have information from all directions. Therefore, three points were defined from the back (Fig. 1f). This could be implemented e.g. by measuring the bed level and using this information as a constrain in the registration. Also, four points were located on the shoulders (Fig. 1f).

2.3 Affine Registration

Prior to non-rigid registration, an *a priori* surface model and target's surface points must be registered using a more constrained, such as rigid or affine, transformation to remove external variations from the data. In this study, we tested both seven-parameter (translation, rotation and isotropic scaling) and nine-parameter (translation, rotation and an-isotropic scaling) affine transformation. A software tool combining surface- and landmark-based registration techniques was used [8]. The energy term to be minimized was defined as $E_{surf} + \alpha E_{mrk}$, where α was a user specified weight. The energy component E_{surf} determined the mean distance of target's surface points from an *a priori* surface model, while E_{mrk} was the mean distance of corresponding anatomical landmarks in both data sets. The minimum of the energy function was searched by a parameter grid technique, which was based on forking the registration parameter space [9]. For the thorax studied in this work, only a few anatomical landmarks could be defined, such as the heads of clavicles, mammary papillae and navel. In this work, the heads of clavicles near sternum were used (Fig. 1).



(a) (b) (c) (d) (e) (f)

Fig. 1. The sets of surface points: a) M16, b) M18, c) M28, d) M30, e) M53 and f) the points on the shoulders and in the back. The uppermost point was defined from the head of clavicle. The number after "M" gives the size of the point set

2.4 Non-rigid Registration Using FFD

A software tool based on FFD grid was used to deform non-rigidly an *a priori* surface model [10]. In FFD, the model was deformed by manipulating the locations of underlying grid points. The transformation function $\mathbf{T} : \mathbf{x} \mapsto \mathbf{x}'$ was defined by a tensor product:

$$\mathbf{T}(x, y, z) = \sum_{i=0}^{l} \sum_{j=0}^{m} \sum_{k=0}^{n} Q_{l,i}(x) Q_{m,j}(y) Q_{n,k}(z) \mathbf{P}_{ijk}, \quad (1)$$

where $Q_{l,i}$ was a polynomial basis function and $\mathbf{P}_{ijk}$ the position of the grid point ijk. The energy to be minimized by FFD point displacements was $E_{data} + \gamma E_{model}$. E_{data} was the average distance of target's surface points from an *a priori* surface model. E_{model} regulated the transformation and it could be computed in several ways in the tool; the curvature of the transformation, $\mathbf{T}$, was regularized in this study ($\gamma = 0.5$). The energy minimization was started with a sparse grid ($3 \times 3 \times 3$). After getting the energy minimum for the current grid, the number of grid points was increased.

Because the selection of an *a priori* model used in FFD deformation affects notably on the registration accuracy, three methods to choose the model were evaluated: 1) random selection from a database, 2) use of an average model (Section 2.5), and 3) controlled model selection from a database (Section 2.6).

2.5 Average Model

An average model was constructed from the database using the approach presented in [11]. First, a reference subject was selected and all database subjects were registered with the reference subject using the seven-parameter affine registration. Next, the reference subject was non-rigidly registered to all database subjects using a surface-based registration algorithm similar to [10]. The average model was achieved by computing an average deformation field and applying this field to the surface model of the reference subject.

2.6 Non-rigid Registration Using FFD with Model Selection

In the model selection [12], the most similar subject to a target was chosen from the database, and its surface model was used as an *a priori* surface model in the non-rigid registration. The similarity was measured based on features computed for each database subject.

The features were computed from the surface points of a target and a database subject after initial (affine) registration: distances between corresponding surface points of the database subject and the target, distances of the target's surface points from the database subject's torso surface, and differences in the surface points' coordinates of the target and the database subject. The similarity measure was a weighted linear combination of the features, where the weights were optimized using regression analysis: the features were used as independent variables and the registration error was used as a dependent variable.

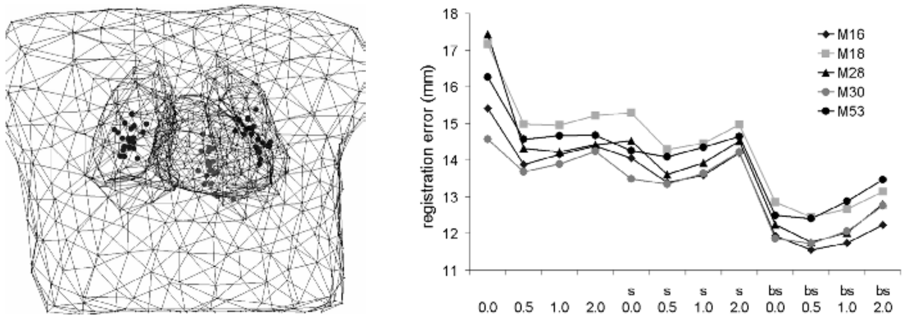
The position and size of the lungs and heart can vary a lot, even if the torso surfaces were registered (Fig. 2a). Therefore, separate model selections for the torso and the internal organs were tested, i.e., the torso surface and the surface of the internal organs of an *a priori* model were selected from different subjects.

2.7 Corrections of Internal Organs

Since the registration was based only on the information from the torso surface, the internal organs could be inaccurately registered. Therefore, we studied if the size and position of the internal organs could be estimated from the shape of the torso surface. The size and mass center of the internal organs were determined for each database subject. After the initial registration, new (approximate) values for the size and mass center were calculated based on the transformation parameters. The errors of these measures between database subjects and a target were calculated and used as dependent variables in four regression analyses (one for the size, and one for the x-, y- and z-directions). The regression analyses were performed in the same way as in the model selection. The regression analyses gave the estimates for the errors in the size and the position of the mass center, and the internal organs were transformed according to these estimates.

2.8 Non-rigid Registration Using Statistical Deformation Model

Active shape model (ASM) [13] is a standard approach to deform a surface model in a way that follows the variability of the shape in the database. In this study, the



(a) (b)

Fig. 2. a) The mass centers of the internal organs of the database subjects after seven-parameter affine registration into a same coordinate system. The average size of the internal organs was 2.3 dm^3 and the standard deviation was 0.6 dm^3. b) The average registration errors of the torso surface for the seven-parameter affine registration. "s" means that the points on the shoulders, and "b" that the points in the back were used in the registration. The weights α for the energy component E_{mrk} (Section 2.3) are given in the lower row

deformation could be defined only for one surface from which the points were digitized but the transformation should have been applied to all surfaces of the model, i.e. the transformation should have been volumetric. Therefore, a statistical deformation model (SDM) [11] was computed from the data produced in Section 2.5. Instead of computing the covariance of the surface model points, as in ASM, the covariance of the deformation field, $\mathbf{T} : \mathbf{x} \mapsto \mathbf{x}'$, was determined in SDM. The deformation fields were defined for a FFD grid of size $15 \times 15 \times 10$. The principal modes of the variation of the deformation field were determined as the eigenvectors of the covariance matrix computed for the FFD grid points.

The deformation of the average model was defined as a weighted sum of the eigenvectors. In the non-rigid registration, the problem was to find the optimal weights, $\mathbf{b}$, for the eigenvectors. In this study, the minimization of energy function $E = E(\mathbf{b})$ was used. The energy described the average distance of target's surface points from the deformed average surface model. A fast and relatively efficient minimization strategy was used: the weights b_i were changed in random order until the energy minimum was found. The procedure was repeated 50 times and the solution producing the lowest energy was chosen. The number of the eigenvectors used in the registration was determined so that 95% of the variance of the database was included in the eigenvectors.

3 Results

The studies were done using full leave-one-out cross-validation, i.e., each subject ($N = 22$) was once regarded as a target and remaining 21 subjects composed the database. The results reported here are average values over all 22 targets. The registration error was determined as an average distance from the manually segmented target surface (from the nodes of the triangle surface) to a spatially transformed *a priori* surface model. In all studies, the internal organs were treated as a one object to avoid topological problems.

Table 1. The registration errors (mm) for different registration methods. Columns from the left: 7-parameter affine (7A) and 9-parameter affine (9A) registration, 7-parameter affine registration using average models (7AA), non-rigid registration with the biggest grid size of $3 \times 3 \times 3$ (F3), $7 \times 7 \times 7$ (F7) and $12 \times 12 \times 12$ (F12), non-rigid registration using average models (F12A, F12AS, see text), registrations with model selections and corrections (M1, M2, M3 and M3S, see text), and registration using SDMs. In the non-rigid registrations, the seven-parameter affine registration was used as an initialization

	7A	9A	7AA	F3	F7	F12	F12A	F12AS	M1	M2	M3	M3S	SDM
torso	11.56	11.24	9.17	8.66	8.23	8.22	6.99	7.15	6.34	6.34	6.34	6.40	7.92
int. org.	14.16	14.30	10.56	14.37	14.26	14.24	10.62	11.13	12.04	11.52	9.68	8.88	10.28
total	12.86	12.77	9.86	11.52	11.25	11.23	8.80	9.14	9.19	8.93	8.01	7.64	9.10

3.1 Set of Surface Points

The average registration errors of the torso surface for different point sets and for different weights for the anatomical landmark, the head of clavicle, are presented in Fig. 2b for the seven-parameter affine registration. A similar figure was achieved for the internal organs, too. The difference between the point sets producing the smallest and the biggest error was about 6 mm of the total error of about 14 mm indicating the importance of the point selection. In practice, the distribution of the surface points appeared to be more important than the number of the points: the registration error of the set M53 ($\alpha = 0.0$) (16.3 mm, 53 points) was bigger than the error of the set M16bs ($\alpha = 0.5$) (11.6 mm, 23 points).

For further studies, the surface point set M16bs and weight $\alpha = 0.5$ were selected. Same studies were done using the point set M30bs, too, but no big differences existed.

3.2 Registration Methods

The registration errors (average values over all 22 targets) for different registration methods are presented in Table 1. In 7A, 9A, F3, F7 and F12, an *a priori* model was selected randomly from the database. In practice, each database subject was once regarded as an *a priori* model in the registration and the average error of these registrations was calculated.

For the torso, the less constrained transformation was used the better results were obtained, but at the same time the results for the internal organs were unchanged. In the non-rigid registration using FFD, the best attainable error was achieved already with a quite moderate maximum grid size: increasing the size above $7 \times 7 \times 7$ did not increase the accuracy.

The use of the average models improved the average results notably, both in the affine (7AA) and non-rigid (F12A) registration. However, the errors of the average models were bigger than the minimum errors of the individual subjects. If we had been able to select from the database the subject which gave the best registration, the individual subjects would have given smaller registration errors than the average models. Results for different model selection procedures and for the corrections of the internal organs are presented in columns M1, M2 and M3. The model selected for the torso was used also for

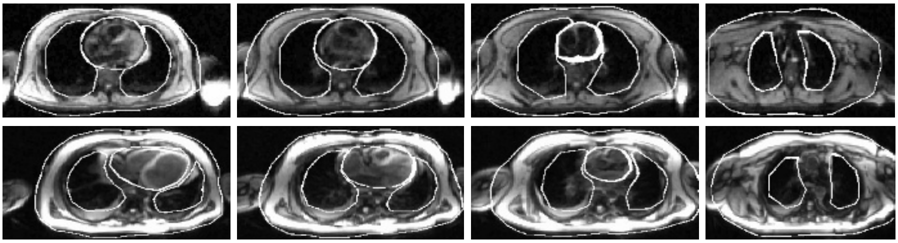


Fig. 3. The best (upper row) and the worst (lower row) registration (M3S) for males

the internal organs in M1, and separate model selections for the torso and internal organs were done in M2 and M3. In all cases, the non-rigid registration F12 was performed for the torso surface. For the internal organs, only the seven-parameter affine registration was done in M1 and M2, but in M3 the surfaces were furthermore transformed using the method presented in Section 2.7. Both the separate model selections and the corrections improved the registration accuracy. The total error of SDMs was worse than the error of the average models or the best model selection procedure.

Above, no difference was made between males and females. However, there are quite big differences in the thorax geometry of males and females. Hence, the database was divided in two parts. When separate average models were constructed for males and females, the average total error (F12AS) was bigger than when a common average model was used (F12A), indicating that the database must be big enough when an average model is used. The model selections and the corrections of the internal organs performed better when the database was divided (M3S). In fact this was the best studied method (Fig. 3). Especially, the error of the internal organs decreased.

4 Conclusion

In this work, different methods to build a geometric model using only a set of surface points were compared. The number of surface points was not highly crucial, but they had to be as uniformly distributed as possible. A reasonable weight ($\alpha \approx 0.5$) for the anatomical landmark improved the results, indicating that the extra information from accurate anatomical landmarks should be used. The best studied method was the non-rigid registration using FFD with both the model selection and the corrections of the internal organs.

It is evident that the database used in this study was too small and hence the statistical models could not model accurately possible variations in the organs' shape and position. If the database had included all possible shapes, SDMs would have given much more accurate results. Naturally, the model selection procedures would have given better results in that case, too.

Obviously, a user can be more confident of the location and size of the internal organs in the model built from an MR volume image than from a few surface points. However, the methods tested provide a good approximation of the geometry if only very limited geometric information is available.

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