Towards Model-based 3-D Reconstruction of the Human Rib Cage from Radiographs

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Abstract :

This work is concerned with the three-dimensional (3-d) shape and pose reconstruction of the human rib cage from few two-dimensional (2-d) radiographs. The reconstruction method is based on a statistical shape model of the rib cage that is adapted to the 2-d image data of a patient. An underlying optimization process minimizes a distance measure which quantifies the dissimilarities between 2-d projections of the 3-d shape model and the X-ray images and thereby estimates the shape model's parameters. We propose a distance measure especially suited for the topology of the rib cage. A validation was performed on 29 sets of simulated, biplanar X-ray images.

Keywords: rib cage, geometry reconstruction, statistical shape model, biplanar X-ray images

1 Problem

In clinical routine, radiography is an inexpensive and frequently used imaging technique for screening and diagnosis of the chest region. Nevertheless, there is a demand for obtaining information on the 3-d chest anatomy of a patient, e.g. for the purpose of simulation and analysis. Interval studies using chest radiographs are widely used to observe the course of a disease. Varying postures of a patient during the image acquisitions, however, pose difficulties to automated diagnosis methods, due to considerable difference in the X-ray images. Since bones are rigid structures, they can be used as a reference system to compensate for these differences. This in turn requires the correct reconstruction of a patient's individual thorax geometry.
In case 3-d information on patient specific anatomy is needed, a 3-d reconstruction from few 2-d radiographs would be a valuable alternative to an expensive tomographic acquisition of 3-d image data with high radiation exposure.

In recent years, several methods were introduced for the 3-d reconstruction of shape [1, 2, 7] and pose [3, 4] information from 2-d images. In [2] a method is proposed to detect and classify shape deformities of the spinal column from X-ray images using a probabilistic prior model. Methods presented in [1] and [7] were used to recover the shape of the femur. The work of [3] deals with determining position and orientation of arbitrary shapes for intra patient registration of X-ray images. In [4] an extended iterative closest point algorithm (ICP) for pose estimations is presented.

The present work addresses the problem of reconstructing the 3-d position, orientation, size (spatial pose) and shape of the rib cage from few 2-d projection images. It is based on a method that uses a 3-d statistical shape model (SSM) for the reconstruction of complex 3-d geometries from synthetic X-ray images [6]. Here, only the shape of the geometry is reconstructed. In addition to the mere reconstruction of the shape, the determination of a patient specific anatomy requires a fair estimation of its pose with respect to a known image acquisition setup. To this end, we extend the aforementioned shape reconstruction method to allow for a 3-d pose estimation of a patient specific rib cage from biplanar, synthetic X-ray images besides the shape reconstruction. Moreover, enhancements are to be proposed that consider the distinct and complex topology of the rib cage.

2 Methods

The reconstruction process is based on a SSM of the ribs that was created from 29 rib cage models, automatically segmented from CT-data [5]. The SSM captures the average shape of the training set as well as its variability in the form of 28 shape modes. The degrees of freedom of this model are its shape weights and its pose parameters .

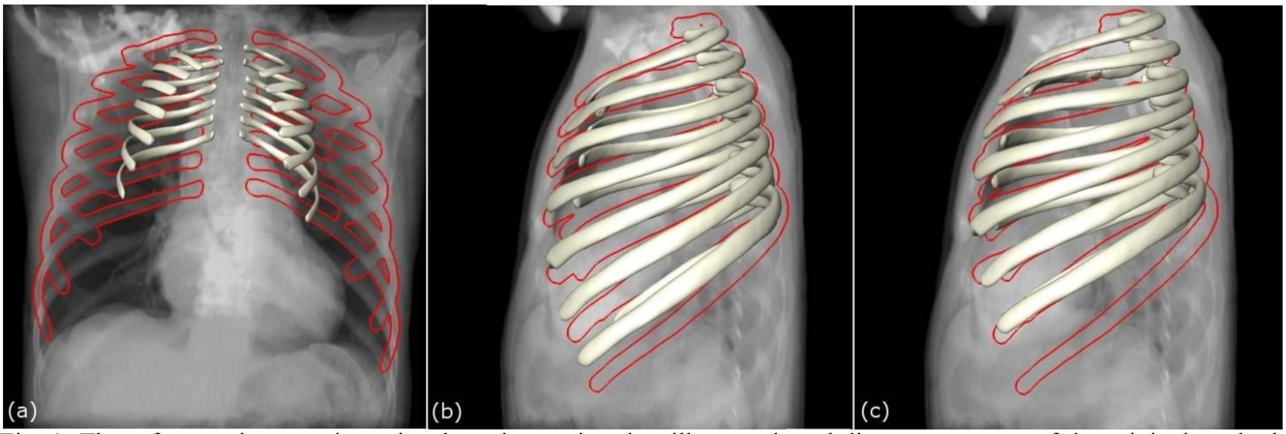

Fig. 1: Three frequently emerging mis-adaptations using the silhouette-based distance measure of the original method: (a) incorrect scaling, (b) contour mismatches (see lowest rib), and (c) mis-assignments of ribs.

More precisely, $T = (t_x, t_y, t_z, \theta_x, \theta_y, \theta_z, s)$ defines a linear transformation, with parameters of translation, rotation and uniform scaling, between the local coordinate system of the SSM and a reference coordinate system. The resulting model is given by $S(b,T) = T(\bar{v} + \sum_{i=1}^{n} b_i p_i)$, where $\bar{v}$ is the average shape and p_i are the shape modes.
The reconstruction of an individual patient's rib cage is achieved by fitting the projection of the SSM to image features within the radiographs. The model's shape and pose parameters are determined by an optimization process that minimizes a distance measure, which is defined on discriminative image features, e.g. silhouettes of the projections of the shape model and rib boundaries in the image data.

A silhouette based distance measure as proposed in [6] was found to be unsuitable for the reconstruction of the pose and the shape of a rib cage. Due to the self-similar topology of the rib cage with its periodically reoccurring ribs, possible mismatches of projected silhouettes to rib boundaries are induced. In particular, three distinct problems were identified: Scale factors are determined incorrectly (see Fig. 1(a)), mismatches of non-corresponding rib contours emerge (see Fig. 1(b)) and mis-assignments of ribs occur (see Fig. 1(c)).

To avoid contour mismatches, we extended the distance measure to take into account the orientation of the silhouette's contour normals. As illustrated in Fig. 2(a), the orientation differences of normals' along two rib contours indicate a mismatch. In addition, a measure of the relative area difference of the silhouettes has been incorporated into the objective function to control the adaptation of the scaling.
For a silhouette S_m in the projection of the SSM and a given silhouette S_r in the X-ray image of the rib cage to be reconstructed, the extended distance measure is defined as follows. The distance d of a point $x_m \in S_m$ to the silhouette S_r is defined by

$$d(x_m, S_r) = \min_{x_r \in S_r} ((1+e)(2-n)(2-a)^2),$$

where $e = \|x_r - x_m\|$ is the Euclidean distance between two points $x_r \in S_r$ and $x_m \in S_m$. $n = n_r \cdot n_m$ denotes the inner product of two silhouette contour normals at points x_r and x_m. It serves as a measure of the orientation difference of both normals. The relative difference a of the areas enclosed by the silhouettes S_r and S_m is defined by the quotient of both areas. The objective function to be minimized is then given by the integrated asymmetric distance

$$D = \int_{x_m \in S_m} d(x_m, S_r)^2 \, dx_m$$

For the optimization of D a gradient-based optimization procedure, that uses improved search directions, was applied (see [6]).

The extension of the distance measure supports a correct assessment of the scaling and prevents mismatches of silhouette contours to rib boundaries. However, mis-assignments of ribs occasionally still occur (cf. lower ribs in Fig.1(c)). In order to overcome the problem of these mis-assignments, we fitted only a subset of ribs to the image data for the initialization of the pose. The ribs corresponding to this subset were labeled in the image data. Since mutual occlusions of ribs in the projections promote mis-assignments, the rib silhouettes within the projection images of such a subset are required to be free from occlusion. For this reason, they should be spatially located as far apart from each other as possible in both projections (see Fig. 2(b)). A subsequent pose and shape reconstruction was performed using the entire set of ribs.

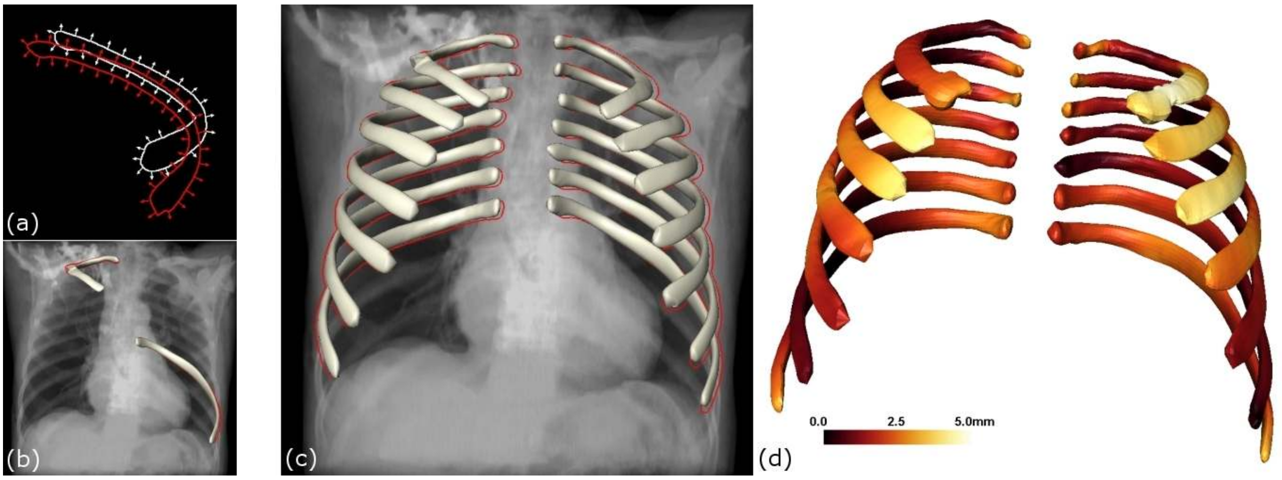

Fig. 2: Two extensions to the method and results. Extensions: (a) The different orientations of silhouette normals indicate contour mismatches, and (b) a subset of ribs is used for the initialization of the pose. Results: In (c) and (d) results of a pose estimation and a shape reconstruction are illustrated.

3 Results

In a first analysis we evaluated the accuracy of the pose and the shape reconstruction separately. In order to appraise the reconstruction quality, we generated pairs of synthetic, biplanar X-ray images to which the shape model was fitted. We measured the reconstruction quality in both cases in 3-d via the mean surface distance between the adapted SSM and a reference surface, which was extracted from the CT data and describes the correct pose as well as the shape in the synthetic X-ray images. The surface distance is computed between corresponding points of both surfaces. The following reconstruction results are given by the averaged and maximum mean surface distance across the individual reconstructions.

Pose Reconstruction. To determine the quality of the pose estimation, we adapted a patient specific rib model with different, random pose initializations to the image pair of the corresponding patient geometry. Ideally the surface distance and the error δT of all pose parameters for such pose estimation would reduce to zero.
We obtain an average of 0.55mm (max 1.15mm) mean surface distance. The corresponding average error of the pose parameters is $\delta\overline{T} = (0.38mm, 0.80mm, 0.24mm, 0.13°, 0.37°, 0.86°, 0.0023)$. Each component of $\delta\overline{T}$ specifies the deviation of a pose parameter from the correct pose of the reference surface extracted from the CT data. The error is averaged across the individual pose estimations. Fig. 2(c) depicts an example result of one individual pose estimation.

Shape Reconstruction. All shape reconstructions were performed with a shape model which excludes the shape to be reconstructed from the set of trainings shapes (leave-one-out test). To assess the optimal value obtainable with this SSM as a reference value, we performed direct surface optimizations in 3-d by minimizing the distance between the SSM and the reference surfaces. This leave-one-out-test results in a mean surface distance of 1.60mm (max. 2.85mm).
For the evaluation of the 3-d shape reconstruction from 2-d image data, the SSM was adapted to 29 pairs of synthetic X-ray images with a given, correct pose of the CT data. The shape reconstructions of the specific rib cages yield an average mean surface distance of 2.53mm (max 4,26mm). Fig. 2(d) exemplifies one shape reconstruction with its deviation from the correct shape.

With the proposed extensions of our method it is possible to avoid incorrect reconstructions that occur using the original method [6]. The 3-d to 3-d leave-one-out test shows that a considerable part of the error is due to the limitation of the SSM's model space. The residual error is presumably due to the mutual occlusion of the ribs in the projection data. The results are comparable to those achieved in the previous work, despite of the topologically more demanding geometry of the rib cage.

Realistic Case. For reconstructing an a-priori unknown geometry from clinical data the simultaneous reconstruction of the shape and pose is mandatory. In a preliminary study on such a combined method the SSM was fitted to one pair of synthetic X-ray images of an unknown rib cage using different random pose initializations. The executed leave-one-out tests resulted in an average mean surface distance of 4.38mm (max 5.47mm).

In some of the individual reconstructions mis-adaptations emerge. We assume that the reason for this lies in the pose estimation approach. It is suitable for recovering a pose if the shape is known in advance. In combination with the shape reconstruction we initially fit the average shape $\overline{v}$ to the image data. Consequently, the final pose of the shape yet to be reconstructed can only be approximated. However, small deviations from the correct pose can cause mis-assignments of ribs driven by the adaptation of the shape weights. With our proposed solution to use a subset of non-occluding ribs it is not always guaranteed to estimate the correct pose in combination with the shape reconstruction.

4 Discussion

We adapted a method for the reconstruction of 3-d shapes to be applicable to the 3-d pose and shape reconstruction of the complex geometry of the rib cage from 2-d image data. The separate reconstruction of both shape and pose yield promising results. Moreover, the combined method already shows good results. For the separate reconstruction of pose and shape the problems of mis-adaptations could be solved by extending the distance measure. In a combined approach mis-adaptations occasionally still emerge due to the limitations of the pose estimation using the average shape of the SSM.

As future work, the optimization strategy shall be improved in order to prevent mis-adaptation for the combined pose and shape reconstruction. The goal is to increase the robustness and accuracy of the method. To this end, we will analyze the relation of the distance measure D with respect to the values of b and T .

So far we focused on analyzing which image features are suitable for a successful 3-d reconstruction. The choice of the features was made bearing in mind that for an automated reconstruction framework these features need to be extractable from the image data. A follow-up question is how much information can finally be extracted from clinical X-ray images. The present method depends on extracted contours of the rib boundaries. Consequently, a segmentation method for the extraction of the ribs from the X-ray images needs to be devised. Depending on the outcome of the automatic segmentation, the current area based distance measure requires further modifications to cope with noisy or incomplete contours of the ribs.

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