Nonrigid 3-D/2-D Registration of Images Using Statistical Models

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Abstract. This paper presents a new algorithm for reconstruction of 3D shapes using a few x-ray views and a statistical model. In many applications of surgery such as orthopedics, it is desirable to define a surgical planning on 3-D images and then to execute the plan using standard registration techniques and image-guided surgery systems. But the cost, time and x-ray dose associated with standard pre-operative Computed Tomography makes it difficult to use this methodology for rather standard interventions. Instead, we propose to use a few x-ray images generated from a C-Arm and to build the 3-D shape of the patient bones or organs intra-operatively, by deforming a statistical 3-D model to the contours segmented on the x-ray views. In this paper, we concentrate on the application of our method to bone reconstruction. The algorithm starts from segmented contours of the bone on the x-ray images and an initial estimate of the pose of the 3-D model in the common coordinate system of the set of x-ray projections. The statistical model is made of a few principal modes that are sufficient to represent the normal anatomy. Those modes are built by using a generalization of the Cootes and Taylor method to 3-D surface models, previously published in MICCAI'98 by the authors. Fitting the model to the contours is achieved by using a generalization of the Iterative Closest Point Algorithm to nonrigid 3D/2D registration. For pathological shapes, the statistical model is not valid and subsequent local refinement is necessary. First results are presented for a 3-D statistical model of the distal part of the femur.

1 Introduction

X-ray images are the dominating image modality in the operating room. Due to his anatomical knowledge the surgeon is used to mentally fuse 2D images taken from different view points. However for many applications this mental registration is not sufficient to obtain all necessary information about the anatomical situation to properly perform the surgery. Therefore, since the introduction of Computed Tomography many surgical interventions are preceded by the construction of a CT-based 3D model of the object of interest to provide the surgeon with spatial information which is leaking when using only 2D images. To combine preoperative acquired CT data with intra-operatively acquired X-ray images, marker based or surface based registration methods are usually applied.

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But the CT data acquisition process is associated with several drawbacks: First, the total X-ray dose for the patient raises considerably. Further it significantly increases the overall intervention costs as well as its duration. Therefore it is desirable to infer 3D-information from the 2D X-ray images to facilitate the navigation within the patient and thus allowing to abandon CT data acquisition at least for many standard surgical applications.

In [Hof97] for instance, authors propose to acquire several images using a classical C-arm equipped with an image intensifier and to track the position and orientation of the surgical tools, the image intensifier and a patient's reference with an optical localizer, thus allowing to compute relative movements of the patient or the surgical tools with respect to each acquired image during the intervention. Although this system is a considerable improvement, real 3D information is still missing.

The objective of this paper therefore is to recover the surface of an object using a very limited number (2 - 6) of calibrated X-ray images. We concentrate here on bone reconstruction but the proposed method is also applicable to other anatomical structures.

Image intensifiers are subject to geometric distortions due to non planar shape of the image intensifier and external magnetic fields. Calibration techniques such as the NPBS method [CLSC92] for instance can be used to correct these distortions as well as to compute a pseudo focal point of the source. This calibration is not further addressed in this paper. However full digital X-ray detectors without any geometric distortion [CCD98] begin to appear on the market and are likely to replace the image intensifiers in the future.

The remainder of this paper is organized as follows: In section 2 we give a brief overview about related work and introduce the statistical shape model of Cootes and Taylor. Section 3 presents a generalization of the Iterative Closest Point algorithm [BM92] for contour based 3D/2D registration. Section 4 shows how to efficiently compute matched point pairs by computing the model's contour generators. Section 5 shows how to fit the model to the projection data. Section 6 provides results obtained with simulated data and in Section 7 we draw a short conclusion.

2 Related Work

First considering the simpler case of recovering only the pose parameters of a 3D model from its 2D projections (rigid 2D/3D registration), one can distinguish two different concepts: One type of algorithm is based on contours and requires prior segmentation of the object in the 3D-image as well as in the 2D-image [LS95,FAB94] although in [HSLC95] authors propose a cooperative approach between registration and 2D segmentation. The other concept does not need segmentation and compares the grey value distribution of the 2D-image with the distribution obtained when projecting the 3D-image under current registration parameters [LFK94]. Due to the high computational cost for projecting the 3D image this method is rather slow although in [Wee99] authors recently proposed a promising technique for considerable acceleration by using the shear-warp factorization.

Much less work has been done in the field of nonrigid 3D/2D registration: In [PV97] for instance, authors aim to recover shape from one single X-ray image by exploiting both, geometric and densitometric constraints while making two assumptions: the density of the structure to be recovered is approximately constant and the surface of each structure is smooth. This approach shares ideas from the work of [TWK88]. In [Nik96] authors reconstruct femurs from 2 orthogonal X-ray images. They separate the femur into 3 subparts each of them assumed to be round. They fit cubic parametric surface patches to the subparts and then assemble them to a complete model. For a general overview about image registration techniques see for instance [MV98].

We propose to formulate the shape recovery problem as a nonrigid registration between a deformable shape model and the contour data extracted from the X-ray views. As we aim to recover the shape from very few projections it is necessary to incorporate a priori knowledge. One possibility is to consider models such as deformable superquadrics [MT93], however those models are appropriate to capture shapes defined by many data (the superquadrics convey information about the global shape but this part of the model is not accurate enough for our applications). Similarly, using volumetric deformations with regularization constraints such as octree-splines [SL96] can be expected to preserve the shape of an anatomical structure, but this will be true only in the neighborhood of the available data. The result of those methods is not guaranteed to be a shape that respects the anatomy.

Another approach is to to consider statistically based shape models in order to infer the anatomical information. One well known approach is to use statistical models based on Fourier representations, such as [SD92,SkBG96]. Another method is based on extracting features such as crest-lines and to perform modal analysis on these features [STA96]. A third approach is to consider a statistical model with modal representation based on principal component analysis directly applied to the nodal representation of a mean contour.

Cootes and Taylor [CTCG95] have proposed to use Point Distribution Models (PDM). A PDM is a deformable model built from the statistical analysis of examples of the object being modeled. Given a collection of N 3D training shapes of an object, the Cartesian coordinates of M landmark points are recorded for each image. Each training example is represented by a vector $\mathbf{m} = (x_1, y_1, z_1, ..., x_M, y_M, z_M)$.

After aligning of the training shapes the pointwise mean shape

$$\bar{\mathbf{m}} = \frac{1}{N} \sum_{i=1}^{N} \mathbf{m}_i \qquad (1)$$

is then calculated. Modes of variation are found using Principal Component Analysis (PCA) on the deviations of examples from the mean. These modes are represented by $3M$ orthonormal eigenvectors $\mathbf{e}_i$. A new instance of the shape is generated by adding linear combinations of the t most significant variation vectors to the mean shape:

$$\mathbf{m} = \bar{\mathbf{m}} + \sum_{i=1}^{t} w_i \mathbf{e}_i \tag{2}$$

where w_i is the weighting factor for the i^{th} variation vector. By ensuring $t < 3M$, only the important deformations are extracted, discarding training data noise, and thus object shape and variation can be captured compactly.

A key requirement for building such a model is the collection of several sets with corresponding landmarks from training images. Doing this manually for a 3D model is impractical due to the considerable effort required for image-model registration. In [FL98] the authors present a method which performs an automatic landmark point generation using a template triangle mesh while ensuring point correspondence between the training shapes.

Fig.1 shows the effect of applying ±3 standard deviations of the first two modes to the mean shape of a model constructed of 10 dry femurs.

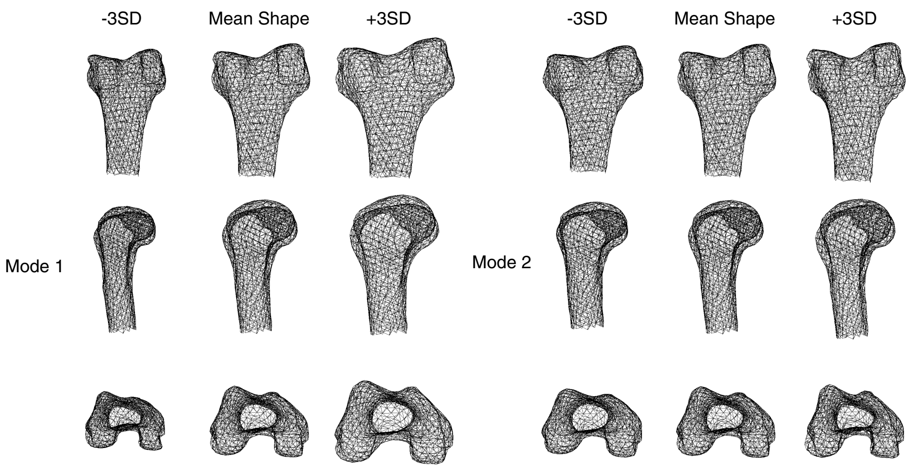


Fig. 1. Applying 3 standard deviations of the first and second deformation modes on the mean shape

3 Using the ICP Algorithm for 2D/3D Registration

A well known method for rigid registration of a 3D data point set with a 3D model point set is the Iterative Closest Point algorithm introduced in [BM92]. Each iteration of the ICP algorithm is divided into two steps. Step 1 establishes point to point correspondence between the data set and the model set. Step 2 calculates a rigid transformation by a direct method using quaternions such that the sum of the squared distances between the corresponding points becomes minimal. To be able to use the ICP algorithm for 3D/2D registration we have to define the correspondence between the model and each projection ray $\mathbf{p}_{i,i=1...P}$ of the X-ray images defined by the coordinates of the contour points x_i, y_i in the image plane and the focal point $\mathbf{f}$ of the source. We associate the endpoints of that line segment originating on the projection ray and ending on the model surface such that their distance to each other is minimal. Note that at each iteration step new points on both, the model and the projection rays may be selected, while in the 3D/3D case the points in the data set remains the same throughout all iterations. In [WH96] authors describe this approach for rigid 2D/3D registration of CAD models to video camera images but do not address the problem of quickly finding those points on the projection ray and the model having the smallest distance to each other. This is a key step for applicability within intra-operative applications. We address this problem in the next section.

4 Efficient Matched Point Pair Building

To efficiently find the above defined correspondence we use the approach described in [Gue98] by first computing the actual contour generators $\mathbf{g}_{i,i=1...G}$ of the model. Contour generators are those object features constituting the (inner and outer) contours of the object in image space with respect to the current projection parameters. As we use a triangle mesh for presentation of our model, the contour generators are a subset of all triangle edges. Thus establishing correspondence results in the simple computation of shortest lines between two 3D line segments. When the model is perfectly aligned with the projection rays, the latter intersect those triangle edges previously found to be contour generators. In [Gue98] authors call the contour generators 'apparent contours' and use them for a rigid registration algorithm to match a CT model with fluoroscopic images. We define the triangles in the mesh by pointers to an edge list. Each edge in the edge list points to the two vertices in a vertex list defining the edge. This representation enables us to efficiently compute the contour generators using the following criterion: For each triangle the viewing direction is defined as the vector originating from the center of projection to the triangle centroid. If the triangle normal, defined by the cross product of ordered orientated triangle edges constitutes an obtuse angle with the viewing direction, the triangle is said to be visible and invisible otherwise. An edge is a contour generator if the triangle on one side of the edge is visible and the triangle on the other side of the edge is invisible. We store all edges meeting this criterion in a list and rather than performing brutal force search within the complete edge list of the model we only have to search within this subset to find matched point pairs. For our model, consisting of about 5000 edges there are only about 300 contour generators for each perspective projection. Fig 2 shows the correspondence between one projection ray and the current contour generators of the model.

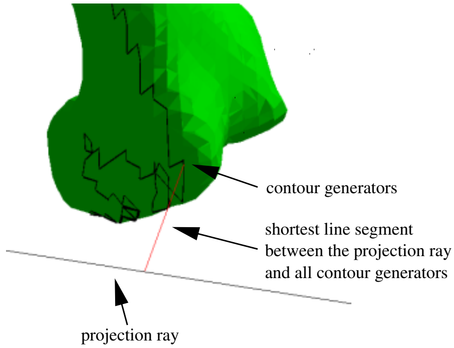


Fig. 2. Correspondence between one projection ray and the current contour generators of the model

5 Model Fitting

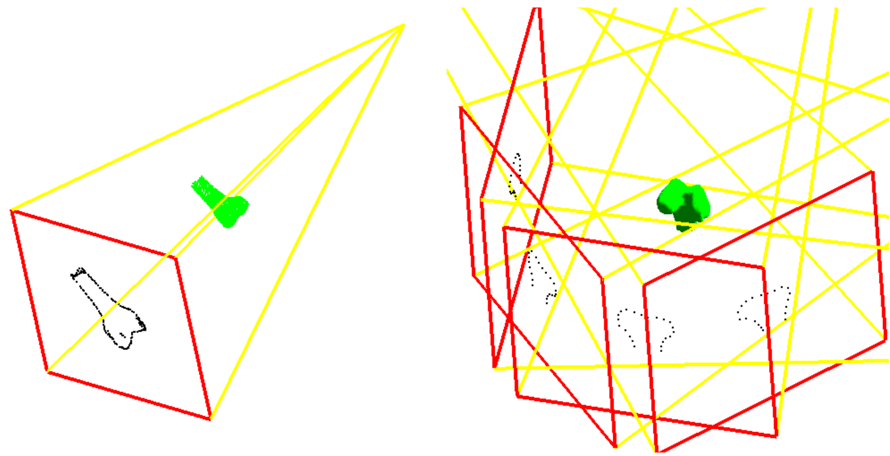
To recover the shape from the projection rays it is necessary to find the rigid transformation (rotation $\mathbf{R}$, translation $\mathbf{T}$) between the matched point pairs and the decomposition of the t preserved eigenvectors in such a way that the distances between them are minimized. The objective function to be minimized is defined as follows:

$$E(\mathbf{R}, \mathbf{T}, w_1 ... w_t) = \sum_{j=1}^{P} \min_{1 \leq k \leq G} \|\mathbf{p}_j - (\mathbf{R}\mathbf{g}_k(w_1 ... w_t) + \mathbf{T})\|^2 \quad (3)$$

In theory, we could simultaneously optimize the rigid and the nonrigid parameters. However, in practise we have found it more efficient to adjust them sequentially. Given an estimate for the pose parameters $\mathbf{R}, \mathbf{T}$ by applying the generalized ICP algorithm we adjust the deformation parameters $w_1 ... w_t$ using the Down Hill Simplex Algorithm. Bounds to the deformation parameters are applied to force the model to deform only in an anatomical reasonable range.

6 Results

Experiments with simulated data have been established using a simulator tool allowing to interactively rotate and translate a 3D model of the distal part of a femur, to project its contour generators onto an image plane and to record the image together with the projection parameters (Fig. 3 a). Fig 3 (b) shows 4 simulated X-ray shots taken from different view points around the object. The experiments were performed using an image plane / focal point distance of 1000mm thus roughly approximating real conditions when using a C-arm. Fig 4 shows the shape model before registration (a), after rigid (b) and after nonrigid (c) registration. One recognizes that the projection rays are tangential to the object surface after the nonrigid registration.



(a) (b)

Fig. 3. (a) Interactive X-ray simulation to compute contours under known perspective projection parameters. (b) Four simulated X-ray shots taken around the object

Experiments using different numbers of X-ray images and varying numbers of deformation modes show that within the current implementation two orthogonal views and 4 deformation modes establish the best compromise between accuracy and computation time. Table 1 shows registration results for different numbers of calculated projection rays per X-ray image. In this experiment we used 2 orthogonal X-ray views and 4 deformation modes. We calculated the RMS between the projection rays and the model and the RMS between the surface model of the shape to be recovered (reference) and the deformed model.

We also compared the accuracy of our 2D/3D matching algorithm with the 3D/3D registration algorithm presented on MICCAI'98. Approximately 500 points randomly distributed on the surface of the shape to be recovered were first registered rigidly with the mean shape, resulting in a RMS of 2.44mm. The nonrigid registration between the 3D data set of the test femur and the deformable model using 4 deformation modes results in a final RMS of 0.85mm. Using 2 (orthogonal) views, each with about 200 projection rays results in a final RMS between the deformed model and the shape to be recovered of 0.99mm.

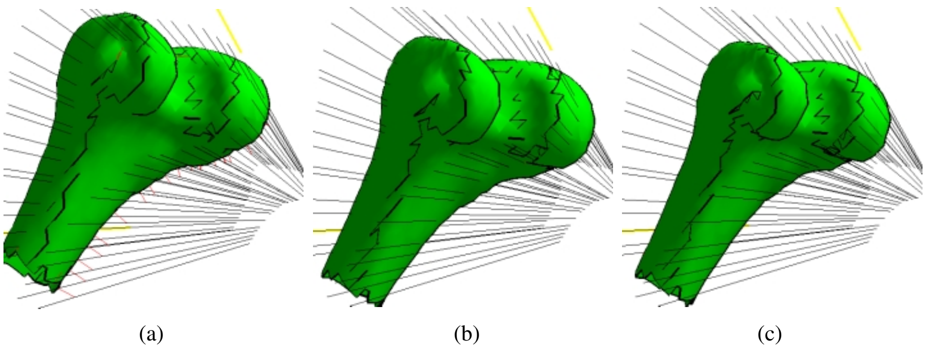


Fig. 4. Surface model of the distal part of the femur: (a) before registration, (b) after initial rigid registration, (c) after nonrigid registration

	RMS (mm)	
rays	rays-model	reference-model
10	0.34	1.3
20	0.52	1.2
50	0.49	1.13
100	0.55	1.05
200	0.77	0.99

Table 1. RMS for different number of projection rays per view

7 Conclusion

Statistical shape models have been proven to be effective for different tasks in the field of computer vision such as segmentation of 2D, 3D images or nonrigid 3D/3D registration. This paper has presented a new approach to perform non-rigid 3D/2D registration between such a model and relatively few segmented contour points from calibrated X-ray images. Contour based registration algorithms suffer from the potential drawback that their accuracy directly depends on the correct segmentation of the objects contour in the image. Our approach is robust with respect to this problem in such a way that good matching results are obtained even when considerable parts of the objects contour cannot reliably be segmented. Computation time of the current implementation directly depends on the number of used projection rays and is less than one minute on a standard workstation when using a total number of 400 projection rays and 4 deformation modes. When dealing with pathological shape deformations which are not covered by the statistical model, local refinements of the model are necessary to obtain a sufficient good fit between the model and the projective data. Experiments with real data acquired with a new distortion free digital X-ray detector (Pixium 4600, Trixell, France) are in progress and will be presented soon.

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