Reconstruction of 3D Lumvar Vertebra from Two X-ray Images Based on 2D/3D Registration

Longwei Fang[1,2], Zuowei Wang[4,5], Zhiqiang Chen[1,2], Fengzeng Jian[4], and Huiguang He[1,2,3](✉)

[1] Research Center for Brain-inspired Intelligence, Institute of Automation, Chinese Academy of Sciences, Beijing, China
huiguang.he@ia.ac.cn
[2] University of Chinese Academy of Sciences, Beijing, China
[3] Center for Excellence in Brain Science and Intelligence Technology, Chinese Academy of Sciences, Beijing, China
[4] Division of Spine, Department of Neurosurgery, Xuanwu Hospital, China International Neurological Institute, Capital Medical University, Beijing, China
[5] Department of Neurosurgery, Beijing Hospital, Beijing, China

Abstract. Constructing a 3D bone from two X-ray images is a challenging task, especially when we would like to build a complicated structure like spine. This paper presents a novel method for reconstructing lumbar vertebra by building correspondence of two X-ray images with a prior model. First, the pose between X-ray images and the vertebra model was estimated; second, the correspondences between the Digitally Reconstructed Radiographies (DRRs) and vertebra model were built; third, the deformation field from DRRs to X-ray images was calculated; last, deformation field was applied to vertebra model to generate the patient's specified 3D model. This method just needs one prior model for 3D reconstruction. The experiments on nine vertebrae of three patients show the average reconstruction error is 1.2 mm (1.0 mm–1.3 mm) which is comparable to the state of the art.

Keywords: 3D reconstruction · Lumbar vertebra model · X-ray images · 2D/3D registration · 2D/2D deformable registration

1 Introduction

Image-guided radiotherapy has been more and more widely used in the hospital. Images shown in 3D form are very useful and convenient for the doctor to understand the pathology. Generally, the Computed Tomography (CT) or Magnetic Resonance Image (MRI) is used to reconstruct the patient's 3D model, however, it is difficult and inconvenient to collect CT/MRI data in operation. Therefore, the technique that use X-ray images to construct patient's 3D model is developed recently [1–7].

J. Yao et al. (Eds.): CSI 2016, LNCS 10182, pp. 125–134, 2016.
DOI: 10.1007/978-3-319-55050-3_12

Statistical Shape Model (SSM) or Point Distribution Model (PDM) was widely used [1–4] for 3D reconstruction. Zheng et al. [5] used two X-ray images and a PDM to construct distal femur. Contours of the surface defined by the PDM were projected into two 2D planes and established correspondences with features detected from fluoroscopic images; these contour points were then back-projected into 3D space, reconstructed into 3D points; then those points were registered to the corresponding 3D point set by deforming the point distribution model to generate patient specified model. Prakoonwit et al. [6] reconstructed distal femur using several X-ray images and a SSM by camera calibration technique. The correspondences between X-ray images were built by camera calibration, and then the correspondence points was back-projected into 3D space and reconstructed into 3D point set, then the statistical shape model was deformed by registering to those points. Whitmarsh et al. [3] proposes a method that using statistical shape model combined with statistical density model to reconstruct patient lumbar vertebrae model. In prepare phase, statistical shape model and statistical density model was constructed from a large dataset of QCT scans, in reconstruction phase, the models were simultaneously registered onto the two DXA images by an intensity based 2D/3D registration process, then the optimized registration was found by adjust the parameters of statistical model. This optimized registration model is the reconstructed patient specified model.

There are some deficiencies in existing methods. Only the boundary or profile of the X-ray images were used [1,2,4–6] to restrict the deformation of the SSM or PDM, they do not make good use of the intensity information inside the boundary. Other methods [3,7] use the intensity information of the whole 2D X-ray images, but the construction speed is very slow as they need to calculate the probability distribution of the shape model in each iteration.

The nature of SSM/PDM method is using a large number of collecting data to build a mean model and a set of deformable parameters, then giving those deformable parameters different weights and adding them to mean shape to generate a series of model and choose one that has the minimal difference with specific patient model. Therefore, the accuracy of those reconstruction methods depend heavily on the unknown patient-specific shape variation covered by the SSM/PDM [8]. In real clinic cases, the pathology spine maybe have a strange shape, the SSM or PDM unable to cover an arbitrary pathology. Actually, if we can find a way to calculate the difference between the prior model and the real data, then we can generate the specific patient model by deforming the prior model with those difference, this kind of method do not rely on the coverage of model shape and can handle more complex cases.

In this paper, we propose a novel methods that using two X-ray images and a prior vertebral model to reconstruct the patient specified vertebral. We only use one vertebral model as prior knowledge, all the deformation are completed in 2D images, the 3D reconstruction accuracy is comparable to the state of art, and the reconstruction speed is fast.

This paper is organized as follows. Section 2 presents the details of reconstruction procedure. Section 3 describes the experiment design and the result, the discussion and conclusion is in Sect. 4.

2 Meterials and Methods

2.1 Brief Introduction of Reconstruction

The main idea is that we introduce a prior model into our method, and we estimate the pose, position and the deformation between the X-ray images and the prior model, and then we apply these parameters to deform the prior model to get the final 3D specific patient model. The whole reconstruction process was divided into four parts: First, the pose between X-ray images and the vertebral model was estimated; second, the correspondence between DRRs and vertebral model was built; third, the deformation field from DRRs to X-ray images was calculated; last, deformation field was applied to the vertebra model to generate the patient specified 3D model. Figure 1 is the flow diagram of the whole reconstruction process.

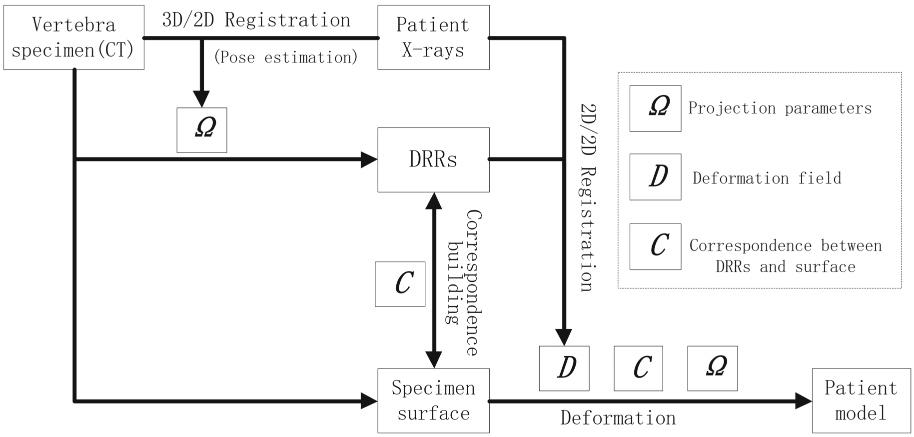

Fig. 1. The flow diagram of the whole reconstruction process

2.2 Data Collection

The CT data of vertebra model or prior model was provided by Beijing Hospital, the model is the third lumbar vertebrae in human body. The data collecting device is GE Discovery HD720, and the resolution of CT is 0.24 mm * 0.24 mm * 0.7 mm. The vertebra specimen is labelled with thirteen landmarks before data collection, six landmarks were posted on vertebra body, one was on spinous process, two were on transverse process and two were on the superior articular process. Figure 2(a) shows the picture of landmarks on vertebra model and Fig. 2(b) is the reconstructed 3D CT image of vertebra model.

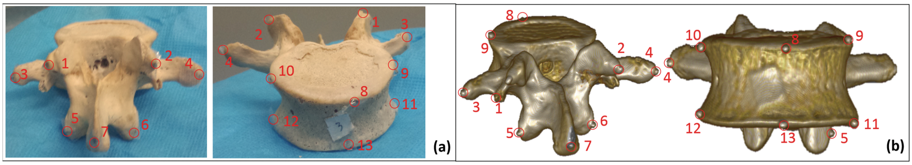

Fig. 2. Landmarks position on vertebra model (a) Landmarks on physical model (b) landmarks on reconstructed CT images

2.3 Pose Estimation Between X-ray Images and Vertebra Model

The projection parameters are the position and pose of the two ray sources when combining the X-ray images and the lumbar vertebra CT into the same coordinate. Two steps were needed to estimate the projection parameters: the reconstructed lumbar vertebrae was segmented from X-ray images and the landmarks were labelled on the segmented images; and the landmarks based 2D/3D rigid registration between X-ray images and the vertebra model. Figure 3(a) shows the calculation procedure of projection parameters. We used the Intelligent Scissors [9] to segment the vertebra. After segmentation, landmarks should be labeled on the segmented image according to the markers position on vertebra model shown in Fig. 2(a). We just labeled the landmarks that can be seen on the segmented image, the landmarks labeled in two images can be different.

We assumed that the distance of the CT center to projection plane is fixed. V_{pc}^i, V_{ps}^i represent the projection of landmarks on coronal and sagittal plane, separately; V_{xc}^i, V_{xs}^i represent the landmarks of X-ray images on coronal and sagittal plane, separately. We assumed that the distance of the ray source to projection plane is d, then we can use Eq. 1 to solve the projection parameters.

$$\Omega = \underset{\Omega=(\Omega_1,\Omega_2)}{\arg\max} \left(\sum_i^M \| V_{pc}^i(\Omega_1) - V_{xc}^i \|^2 + \sum_j^N \| V_{ps}^j(\Omega_2) - V_{xs}^j \|^2 \right) \tag{1}$$

In Eq. (1), the origin of coordinate system is the center of CT data, $\| \cdot \|$ is the Euclidean distance; $\Omega_1 = \{r_{x1}, r_{y1}, r_{z1}, t_{x1}, t_{z1}\}$, $\Omega_1 = \{r_{x2}, r_{y2}, r_{z2}, t_{x2}, t_{z2}\}$ is the projection parameters of two ray source; r_{x*}, r_{y*}, r_{z*} is the rotate angle along three axis, t_{x*}, t_{z*} is the translation along x and z axis; M represents the landmarks on coronal plane, N represents the landmarks on sagittal plane.

2.4 Building Correspondence Between Projection Images and Vertebra Model

This process could be achieved by three steps: vertebra model surface extraction, DRRs generation, projecting control points into DRRs. Figure 3(b) shows the correspondence building between projection images and vertebra model.

First, the surface of the lumbar vertebra model was extracted. The vertexes of the mesh were the control points which were used to reconstruct the patient specified vertebra model. The number of the vertices was 3500.

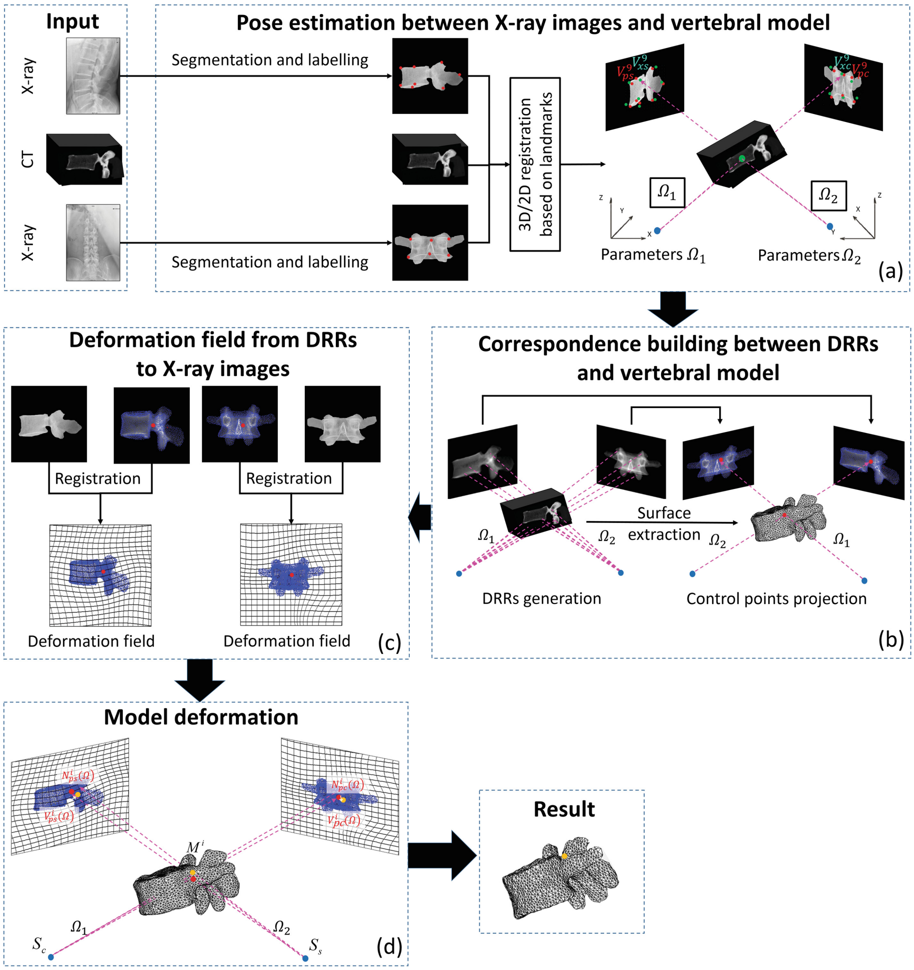

Fig. 3. The flow chart of whole reconstruction process (a) shows the pose estimation between X-ray images and vertebra model (b) shows the correspondence built between DRRs and vertebra model (c) shows the flow chart of calculating deformation field (d) shows the process of model deformation to generate the specific patient model

Second, projection images or DRRs were generated by projecting the CT data into projection planes. We used the ray casting algorithm [10] to generate the DRRs. Figure 4(a) shows the DRRs in coronal and sagittal plane, separately.

Last, the intersection coordinates that lines which are Connect the ray source and control points with projection planes (DRRs plane) were calculated. Dividing the intersection coordinates by the pixel space and rounding the result, we will find the correspondence location on the DRRs for the projection of the control points. The projection of the same control point in two planes are a control point pair and the projection of control points moved when the correspondence

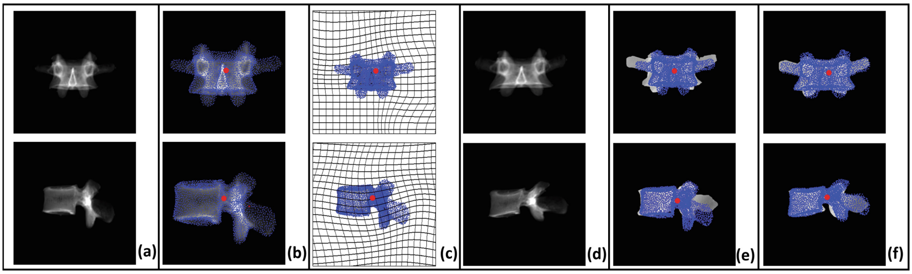

Fig. 4. The intermediate result of calculating deformation field of projection images (a) DRRs generated from CT data (b) projection of control points (c) deformation field after deformable registration, we change the background into white for clearly showing the deformation field (d) results of deformation on DRRs (e) projection of control points mapping in X-ray images before registration (f) projection of control points mapping in X-ray images after registration. The red dots in above images are the projection of same control point (Color figure online)

pixels in DRRs moved. Figure 4(b) shows the projection of the control points in the coronal and sagittal plane separately, the reds ones are the projection of a same control point.

2.5 Calculating the Deformation Field from DRRs to X-ray Images

The deformation field from DRRs to X-ray images was calculated by Free-Form Deformation registration method [11]. Figure 3(c) shows the flow chart of calculation. Figure 4(c) is the deformation field after registration, Fig. 4(d) is the deformation result of DRRs, Fig. 4(e) is the projection of control points mapping into the X-ray images before registration and Fig. 4(f) is the projection of control points mapping in the X-ray images after registration.

2.6 Model Deformation

We assume $V_{pc}^i(\Omega)$, $V_{ps}^i(\Omega)$ are the projection of the same control point in coronal and sagittal plane separately, where $V_{pc}^i(\Omega) = [x_c^i, y_c^i]^T$, $V_{ps}^i(\Omega) = [x_s^i, y_s^i]^T$; D_{pc}^i, D_{ps}^i represent deformation vector in coronal projection image and sagittal projection image separately, where $D_{pc}^i = [d_{cx}^i, d_{cy}^i]^T$, $D_{ps}^i = [d_{sx}^i, d_{sy}^i]^T$; and $[d_{*x}, d_{*y}]^T$ is the deformation in position $[x, y]^T$. N_{pc}^i, N_{ps}^i are the new position of control point's projection after deformation in two planes. Then we have

$$\begin{cases} N_{pc}^i = V_{pc}^i(\Omega) + D_{pc}^i = [x_c^i + d_{cx}^i, y_c^i + d_{cy}^i]^T \\ N_{ps}^i = V_{ps}^i(\Omega) + D_{ps}^i = [x_s^i + d_{sx}^i, y_s^i + d_{sy}^i]^T \end{cases} \tag{2}$$

The intersection point M^i by the line $S_c N_{pc}^i(\Omega)$ and line $S_s N_{ps}^i(\Omega)$ is the new position of the control point i. Figure 3(d) shows the deformation of vertebra model.

3 Experiments and Results

3.1 Experiments Design

The X-ray images of three patients were used to validate the method, and the X-ray images were shown in Fig. 5. L2, L3 and L4 of the lumbar vertebra were chose for reconstruction. We segmented vertebra model from corresponding CT and extracted its surface as the ground truth, the vertex number of the surface was 3500. The average distance from reconstructed mesh to the ground truth was regard as reconstruction error. For the experiment, we used 18 Inter(R) Xeon(R) CPU e5-2687w @3.10 GHz with 64 G RAM, the operation system is CentOS6.3 and the programming language is C++ mixed with MATLAB.

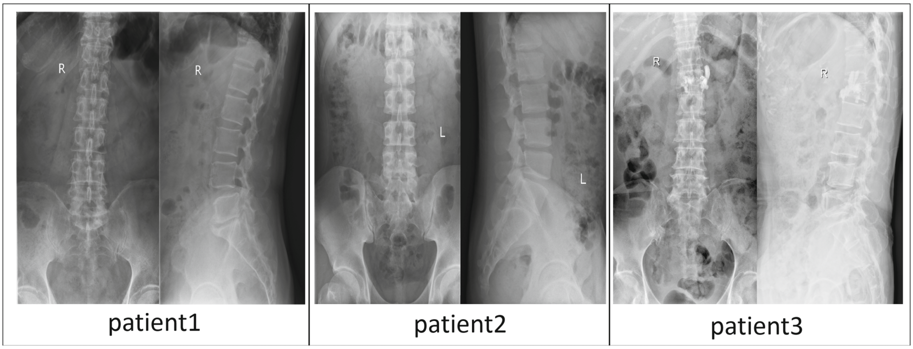

Fig. 5. The X-ray images of three patients

3.2 Result

We used the proposed method to reconstruct L2, L3 and L4 lumbar vertebra successfully, the average reconstruction error was 1.2 mm (1.0 mm–1.3 mm), and the average reconstruction time was 45 s. Table 1 shows the reconstruction error and time of each lumbar vertebra, and Fig. 6 shows the result of reconstruction, for each patient, the left column is the ground truth with the color-coded error distribution; the middle column shows the result of reconstruction; right column is the histogram of the reconstruction error, 95% of the reconstruction error less than the value in red line.

Table 1. Reconstruction error and time of all three patients

Case	P1-L2	P1-L3	P1-L4	P2-L2	P2-L3	P2-L4	P3-L2	P3-L3	P3 -L4
Error (mm)	1.2 ± 1.1	1.3 ± 1.3	1.3 ± 1.0	1.2 ± 1.0	1.2 ± 1.0	1.3 ± 1.2	1.1 ± 0.8	1.0 ± 0.8	1.2 ± 1.0
Time (s)	46	42	43	48	44	45	45	47	44

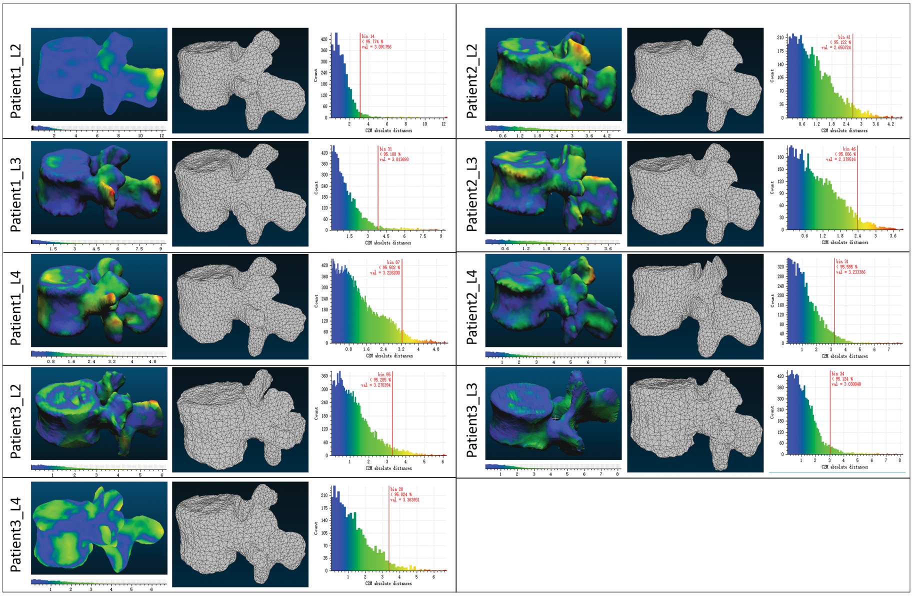

Fig. 6. Reconstruction result. For each patient, left column is ground truth models with the color-coded error distributions; middle column is the reconstruction result, right column is the histogram of the reconstruction error, 95% of the reconstruction error less than the value in red line (Color figure online)

4 Discussion and Conclusion

We proposed a novel method to reconstruct lumbar vertebra with two X-ray images and showed its application on nine lumbar vertebras. This novel method performed reconstruction by building correspondence of two X-ray images with a known lumbar vertebra model, it was tested in nine lumbar vertebras of three patients, the average reconstruction error was 1.2 mm (1.0 mm–1.3 mm) and the average construction time was 45 s. The experiments showed the good performance of our method in reconstruction.

The main difference between the present technique and the other works [1–7] lies in the fact that we use one prior model rather than SSM/PDM to reconstruct the specific patient model. We calculate the difference between the patient images and the prior knowledge and then add this difference to prior model to generate the specific patient model while the SSM/PDM based method build a series model and choose one that has a minimal difference with the patient date. What's more, we use the full information of the X-ray images rather than the boundary information of the information and the iteration process is finished in 2D images in our method, not in the 3D model, so the reconstruction speed is very fast. Moreover, the control points of our method evenly distribute in the whole ROI of the segmented X-ray images, as shown in Fig. 4(f), while the other methods [4–6] just distribute along the boundary of images.

There are some deficiencies in present approach. First, it needs to segment the reconstructed lumbar vertebra from X-ray image and add landmarks manually, although the reconstruction process does not take much time, the segmentation takes a lot of time; second, the reconstruction accuracy depends heavily on 2D/2D deformable registration between X-ray images and DRRs, the reconstruction error will be large when the registration result is not good. Nonetheless, the experiments from the present study demonstrate that this method will be more widely used in the future if it can cooperate with other auto segmentation methods and a more accurate 2D/2D registration method.

Acknowledgements. This work was supported by 863 Projects (2013AA013803), National Natural Science Foundation of China (61271151, 91520202) and Youth Innovation Promotion Association CAS.

References

1. Baka, N., Kaptein, B., de Bruijne, M., van Walsum, T., Giphart, J., Niessen, W.J., Lelieveldt, B.P.: 2D–3D shape reconstruction of the distal femur from stereo X-ray imaging using statistical shape models. Med. Image Anal. **15**(6), 840–850 (2011)
2. Humbert, L., De Guise, J., Aubert, B., Godbout, B., Skalli, W.: 3D reconstruction of the spine from biplanar X-rays using parametric models based on transversal and longitudinal inferences. Med. Eng. Phys. **31**(6), 681–687 (2009)
3. Whitmarsh, T., Humbert, L., Barquero, L.M.D.R., Di Gregorio, S., Frangi, A.F.: 3D reconstruction of the lumbar vertebrae from anteroposterior and lateral dual-energy X-ray absorptiometry. Med. Image Anal. **17**(4), 475–487 (2013)
4. Benameur, S., Mignotte, M., Labelle, H., De Guise, J.A.: A hierarchical statistical modeling approach for the unsupervised 3-D biplanar reconstruction of the scoliotic spine. IEEE Trans. Biomed. Eng. **52**(12), 2041–2057 (2005)
5. Zheng, G., Gollmer, S., Schumann, S., Dong, X., Feilkas, T., Ballester, M.A.G.: A 2D/3D correspondence building method for reconstruction of a patient-specific 3D bone surface model using point distribution models and calibrated X-ray images. Med. Image Anal. **13**(6), 883–899 (2009)
6. Prakoonwit, S.: Towards multiple 3D bone surface identification and reconstruction using few 2D X-ray images for intraoperative applications. Int. J. Art Cult. Des. Technol. **4**, 13–31 (2014)
7. Yao, J., Taylor, R.: Assessing accuracy factors in deformable 2D/3D medical image registration using a statistical pelvis model. In: 2003 Proceedings of the Ninth IEEE International Conference on Computer Vision, pp. 1329–1334. IEEE (2003)
8. Zheng, G., Nolte, L.-P.: Reconstruction of 3D vertebral models from a single 2D lateral fluoroscopic image. In: Li, S., Yao, J. (eds.) Spinal Imaging and Image Analysis. LNCVB, vol. 18, pp. 349–365. Springer, Cham (2015). doi:10.1007/978-3-319-12508-4_11
9. Mortensen, E.N., Barrett, W.A.: Intelligent scissors for image composition. In: Proceedings of the 22nd Annual Conference on Computer Graphics and Interactive Techniques, pp. 191–198. ACM (1995)

10. Jacobs, F., Sundermann, E., De Sutter, B., Christiaens, M., Lemahieu, I.: A fast algorithm to calculate the exact radiological path through a pixel or voxel space. CIT J. Comput. Inf. Technol. **6**(1), 89–94 (2015)
11. Mattes, D., Haynor, D.R., Vesselle, H., Lewellen, T.K., Eubank, W.: PET-CT image registration in the chest using free-form deformations. IEEE Trans. Med. Imaging **22**(1), 120–128 (2003)