An Integrated Approach for Reconstructing Surface Models of the Proximal Femur from Sparse Input Data for Surgical Navigation

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Abstract. A patient-specific surface model of the proximal femur plays an important role in planning and supporting various computer-assisted surgical procedures including total hip replacement, hip resurfacing, and osteotomy of the proximal femur. The common approach to derive 3D models of the proximal femur is to use imaging techniques such as computed tomography (CT) or magnetic resonance imaging (MRI). However, the high logistic effort, the extra radiation (CT-imaging), and the large quantity of data to be acquired and processed make them less functional. In this paper, we present an integrated approach using a multi-level point distribution model (ML-PDM) to reconstruct a patient-specific model of the proximal femur from intra-operatively available sparse data. Results of experiments performed on dry cadaveric bones using dozens of 3D points are presented, as well as experiments using a limited number of 2D X-ray images, which demonstrate promising accuracy of the present approach.

Keywords: surface reconstruction, surgical navigation, X-ray, point distribution model, statistical shape analysis.

1 Introduction

A patient-specific surface model of the proximal femur plays an important role in planning and supporting various computer-assisted surgical procedures including total hip replacement, hip resurfacing, and osteotomy of the proximal femur. The common approach to derive 3D models of the proximal femur is to use imaging technique such as computed tomography (CT) or magnetic resonance imaging (MRI). However, the high logistic effort, the extra radiation associated with the CT-imaging, and the large quantity of data to be acquired and processed make them less functional. The alternative presented here is to reconstruct the surface model using sparse input data consisting of dozens of surface points (e.g. 50 points) or a limited number of calibrated fluoroscopic images (e.g. 2 to 4 images).

Constructing an accurate 3D surface model from sparse input data is a challenging task. Additionally, inherent to the navigation application is the high accuracy and

V.G. Duffy (Ed.): Digital Human Modeling, HCII 2007, LNCS 4561, pp. 767–775, 2007.

robustness requirements. When surface reconstruction is used for the purpose of surgical guidance, it requires that the algorithm satisfies the following criteria: (a) accurate geometrical information about the underlying anatomical structure can be derived from the reconstructed surface model; (b) target reconstruction error of the reconstructed surface model should be in the range of surgical usability, which is typically in the area of 1.5 mm average error (2 to 3 mm worst case) [1]; (c) 95% success rate is normally required, when an appropriate initialization is given [1]; (d) minimal user interaction during data acquisition and algorithm execution is highly appreciated for a sterilized environment; and (e) the algorithm should be robust to outlying data. In the present paper, we try to solve the problem in an accurate and robust way. At the heart of our approach lies the combination of sophisticated surface reconstruction techniques and a multi-level point distribution model (ML-PDM) of the target anatomical structure.

The paper is organized as follows. Section 1 reviews the related work. Section 2 presents the construction of the ML-PDM of the proximal femur. Section 3 describes the integrated approach combining our previous works on 3D-3D surface reconstruction [2, 3] and those on 2D-3D surface reconstruction [4, 5]. Experimental results using both 3D sparse point set as well as 2D X-ray images are described in Section 5, followed by conclusions in Section 6.

2 Related Works

Statistical shape analysis [6, 7, 8] is an important tool for understanding anatomical structures from medical images. A statistical model givens an effective parameterization of the shape variations found in a collection of sample models of a given population. Model based approaches [9, 10, 11] are popular due to their ability to robustly represent objects. Intraoperative reconstruction of a patient-specific model from sparse input data can be potentially achieved through the use of a statistical model. Statistical model building consists of establishing legal variations of shape from a training population. A patient-specific model is then instantiated through fitting the statistical model to intraoperatively acquired data. Thus, the aim of the statistical instantiation is to extrapolate from sparse input data a complete and accurate anatomical representation. This is particularly interesting for minimally invasive surgery (MIS), largely due to the operating theater setup.

Several research groups have explored the methods for reconstruction a patient-specific model from a statistical model and sparse input data such as digitized points [2, 3, 12, 13, 14, 15], a limited number of calibrated X-ray images [4, 5, 16, 17, 18, 19, 20], or tracked ultrasound [21, 22, 23, 24]. Except the method presented by Yao and Taylor [17], which depends on a deformable 2D/3D registration between an appearance based statistical model [25] and a limited number of X-ray images, all other methods have their reliance on a point distribution model (PDM) in common. In Fleute and Lavallée [12], a statistical shape model of the distal femur was fitted to sparse input points by simultaneously optimizing both shape and pose parameters. Their technology has been incorporated into a system for computer-assisted anterior cruciate ligament surgery and preliminary results were published in [13]. Chan et al. [21, 22] used a similar algorithm, but optimized the shape and pose parameters separately. Tracked ultrasound was used as the input in their work to instantiate 3D surface models of the complete femur and pelvis from their associated statistical shape models. Following the seminal work of Blanz and Vetter for the synthesis of 3D faces using a morphable model [26], Rajamani et al. [14, 15, 23] incorporated a Mahalanobis prior for a robust and stable surface model instantiation. In our recent work [2, 3], we proposed to use the dense surface point distribution model (DS-PDM) and a reconstruction scheme combining statistical instantiation and kernel-based deformation for an accurate and robust reconstruction of a patient-specific surface model of the proximal femur from dozens of points. This reconstruction scheme has also been combined with a novel 2D-3D correspondence establishing algorithm [27] for reconstructing surface model of the proximal femur from a limited number of calibrated X-ray images [4, 5].

3 Multi-level Point Distribution Model Construction

The ML-PDM used in this paper was constructed from a training database consisting of 30 proximal femoral surfaces from above the lesser trochanter. In the coarsest level, a sequence of correspondence establishing methods presented in [28] was employed to optimally align surface models segmented from CT volume. It started with a SPHARM-based parametric surface description [29] and then was optimized using Minimum Description Length (MDL) based principle as proposed in [30].

Following the alignment, the PDM in this level is constructed as follows. Let $\mathbf{x}_i = (p_0, p_1, \ldots\ldots, p_{N-1})$, $i = 0, 1, \ldots, m-1$, be m (here m = 30) members of the aligned training surfaces. Each member is described by a vectors $\mathbf{x}_i$ with N (N = 4098) vertices:

$$\mathbf{x}_i = \{x_0, y_0, z_0, x_1, y_1, z_1, \ldots, x_{N-1}, y_{N-1}, z_{N-1}\} \tag{1}$$

The PDM is obtained by applying principal component analysis on these surfaces.

$$\begin{aligned} D &= ((m-1)^{-1}) \cdot \sum\nolimits_{i=0}^{m-1} (\mathbf{x}_i - \overline{\mathbf{x}})(\mathbf{x}_i - \overline{\mathbf{x}})^T \\ P &= (\mathbf{p}_0, \mathbf{p}_1, \ldots); \qquad D \cdot \mathbf{p}_i = \sigma_i^2 \cdot \mathbf{p}_i \end{aligned} \tag{2}$$

Where $\overline{\mathbf{x}}$ and D represents the mean vector and the covariance matrix respectively.

Then, any one of the instance in this space can be expressed as:

$$\mathbf{x} = \overline{\mathbf{x}} + \sum\nolimits_{i=0}^{m-2} \alpha_i \mathbf{p}_i \tag{3}$$

And the estimated normal distribution of the coefficients $\{\alpha_i\}$ is:

$$p(\alpha_0, \alpha_1, \ldots, \alpha_{m-2}) = (2\pi)^{-\frac{m-1}{2}} \cdot e^{-\frac{1}{2}\sum_{i=0}^{m-2}(\alpha_i^2 / \sigma_i^2)} \tag{4}$$

Where $\sum\nolimits_{i=0}^{m-2} (\alpha_i^2 / \sigma_i^2)$ is the Mahalanobis distance defined on the distribution.

The vertices for constructing the denser point distribution model in a finer resolution are then obtained by iteratively subdividing the aligned surface model in the coarser resolution. The basic idea of subdivision is to provide a smooth limit surface model which approximates the input data. Starting from a mesh in a low resolution, the limit surface model is approached by recursively tessellating the mesh. The positions of vertices created by tessellation are computed using a weighted stencil of local vertices. The complexity of the subdivision surface model can be increased until it satisfies the user's requirement.

In this work, we use a simple subdivision scheme called *Loop scheme*, invented by Loop [31], which is based on a spline basis function, called the three-dimensional quartic box spline. The subdivision principle of this scheme is very simple. Three new vertices are inserted to divide a triangle in a coarse resolution to four smaller triangles in a fine resolution.

Loop subdivision does not change the positions of vertices on the input meshes. Furthermore, positions of the inserted vertices in a fine resolution are interpolated from the neighboring vertices in a coarse resolution. As the input surface models have been optimized for establishing correspondences, it is reasonable to conclude that the output models are also aligned. Principal component analysis can be applied on these dense surface models to establish a dense surface point distribution model (DS-PDM). In our previous work [2], we found that a single level subdivision is enough for our purpose, which results in 16386 vertices for each surface model. We thus created a two-level point distribution model (TL-PDM).

4 The Integrated Surface Model Reconstruction Approach

Based on the two-level point distribution model, we developed an integrated surface model reconstruction approach which can seamlessly handle both 3D sparse points and a limited number of X-ray images. When a set of 3D points are used, the fine level point distribution model (FL-PDM) will be chosen, which facilitates the point-to-surface correspondence establishment. But if the input is a limited number of calibrated X-ray images, we will use the coarse level point distribution model (CL-PDM) to speed up the computation. For completeness, we will briefly present these two methods below. Details can be found in our previously published works [2, 3, 4, 5].

3D-3D Reconstruction Method [2, 3]: The reconstruction problem is formulated as a three-stage optimal estimation process. The first stage, *affine registration*, is to iteratively estimate the scale and the 6 degree-of-freedom rigid transformation between the mean shape of the PDM and the sparse input data using a correspondence building algorithm and a variant of iterative closest point (ICP) algorithm [32]. The estimation results of the first stage are used to establish point correspondences for the second stage, *statistical instantiation*, which optimally and robustly instantiates a surface model from the PDM using a statistical approach [14]. The instantiated surface model is taken as the input for the third stage, *deformation*, where the input surface is further deformed by an approximating thin-plate spline (TPS) based vector transform [33] to refine the statistically instantiated surface model.

2D-3D Reconstruction Method [4, 5]: Our 2D-3D reconstruction approach combines statistical instantiation and regularized shape deformation as described above with an iterative image-to-model correspondence establishing algorithm [27]. The image-to-model correspondence is established using a non-rigid 2D point matching process, which iteratively uses a symmetric injective nearest-neighbor mapping operator and 2D thin-plate splines based deformation to find a fraction of best matched 2D point pairs between features detected from the fluoroscopic images and those extracted from the 3D model. The obtained 2D point pairs are then used to set up a set of 3D point pairs such that we turn a 2D-3D reconstruction problem to a 3D-3D one, which can be solved by the 3D-3D reconstruction approach as described above.

5 Experimental Results

We designed and conducted experiments on 18 cadaveric femurs (Note: none of them has been included for constructing the TL-PDM) with different shape to validate the present integrated approach. 3D point sets as well as calibrated X-ray images were used.

Reconstruction error measurement: To quantify the reconstruction error, Target Reconstruction Error (TRE) was used. The TRE is defined as the distance between the actual and the reconstructed position of selected target features, which can be landmark points or bone surfaces themselves.

Validation experiments: Two different types of sparse data were explored in two experiments: (1) using clinically relevant sparse points directly acquired from the surfaces of 7 cadaveric femurs; (2) using a limited number of calibrated fluoroscopic images of the other 11 cadaveric femurs. To evaluate the reconstruction error, we acquired another set of landmarks from each surface of the dry cadaveric femurs (Please note that these landmarks were not used in the reconstruction procedures but for the accuracy evaluation purpose). Then, the TRE was measured by calculating the distances between these landmarks and the associated reconstructed surface model.

Results of the first experiment: Total hip replacement and hip resurfacing procedures operated with posterior approach were identified as the potential clinical applications. At one stage of such surgeries, after internal rotation and posterior dislocation of the hip, most of the femoral head, neck, and some part of trochantric and intertrochantric (crest and line) regions are exposed [34]. Obtaining sparse surface points from these intraoperatively accessible regions and reconstructing a patient-specific 3D surface model of the proximal femur with reasonable accuracy will be useful for the above mentioned surgeries. In this experiment, one set of 50 points was used to reconstruct the surface model of each cadaveric bone and the other set consisted of 200 points was used to evaluate the reconstruction errors. The results of surface reconstruction using clinically relevant sparse points are presented in Fig. 1. For each case, the overall execution time was less than one minute.

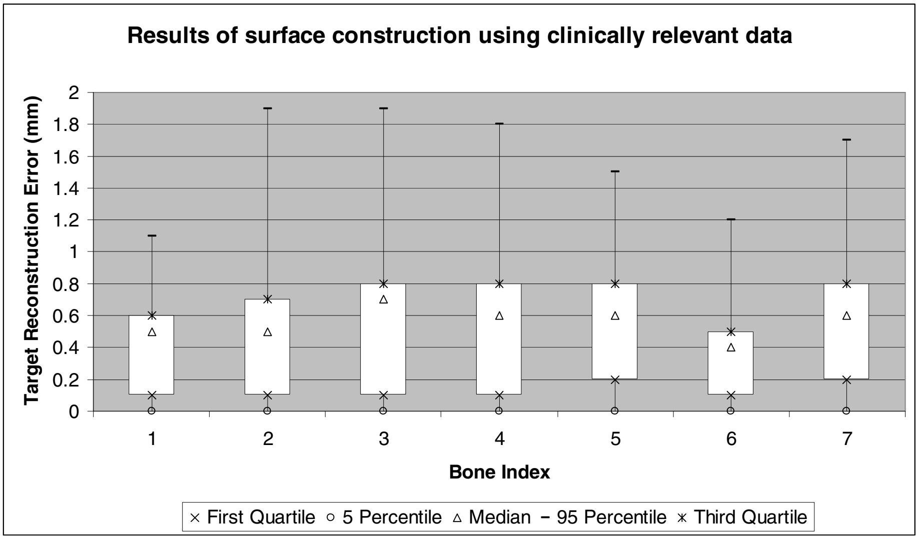

Fig. 1. Errors of reconstructing surface models of seven cadaver femurs using clinically relevant data

Results of the second experiment: In this experiment, two studies using different number of images were performed for each bone. In the first study two images acquired from anterior-posterior (AP) and lateral-medial (LM) directions were used to reconstruct the surface model of each cadaveric femur. In the second one, an image acquired from oblique direction was additionally used together with the above mentioned AP and LM images.

The reconstruction accuracies were evaluated by randomly digitizing 100 – 200 points from each surface of the cadaveric specimen and then computing the distance from those digitized points to the associated surface reconstructed from the images. The median and mean reconstruction errors of both experiments are presented in Table I. An average mean reconstruction error of 1.2 mm was found when only AP and LM images were used for each bone. It decreased to 1.0 mm when three images were used. Different stages of one reconstruction example are presented in Fig. 2.

Table 1. Reconstruction errors when different number of images were used

Reconstruction errors when only AP and LM images were used for each bone											
Bone Index	1	2	3	4	5	6	7	8	9	10	11
Median (mm)	1.3	0.8	1.5	1	1.3	1	1.1	1	0.8	1.1	1.2
Mean (mm)	1.5	0.8	1.4	1.3	1.4	1.2	1.2	1.2	1	1.1	1.6
Reconstruction errors when all three images were used for each bone											
Bone Index	1	2	3	4	5	6	7	8	9	10	11
Median (mm)	1.3	0.7	0.7	1.1	1	1.1	0.8	0.9	0.7	1	0.9
Mean (mm)	1.3	0.7	0.8	1.2	1.1	1.1	1.1	0.9	0.9	1.1	1.2

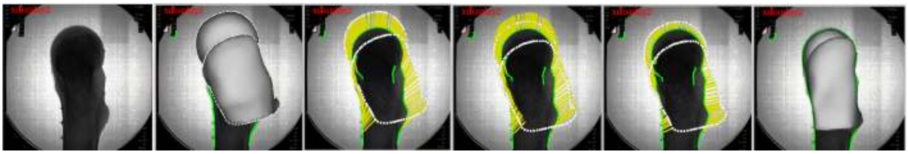

Fig. 2. Different stages of reconstruction. First: one of the acquired images. Second: the initialization of the mean model of the PDM. Third: after establishing image-to-model correspondence. Fourth: after 3D paired point matching. Fifth: after re-establishing correspondence; Sixth: the final reconstruction result after a series of computations.

6 Conclusions

We have presented an integrated approach using the ML-PDM for robust and accurate anatomical shape reconstruction from sparse input data. Based on the modalities of the input data, the appropriate level point distribution model was used. In this approach, the 3D-3D reconstruction problem is formulated as a three-stage optimal estimation process. In each stage, the best result is optimally estimated under the assumption for that stage, which guarantees a topologically preserved solution when only sparse points are available. The FL-PDM is employed in all stages to facilitate the correspondence establishment. When a limited number of calibrated X-ray images are used, the CL-PDM is employed to speed up the computation. A 2D-3D correspondence establishing algorithm based on a non-rigid 2D point matching process is applied to convert a 2D-3D problem to a 3D-3D one.

The proposed approach is generic and can be easily extended to other rigid anatomical structures, though in this paper we only demonstrate its application for reconstructing surface models of the proximal femur.

References

1. Livyatan, H., Yaniv, Z., Joskowicz, Z.: Gradient-based 2-D/3-D rigid registration of fluoroscopic X-ray to CT. IEEE T Med Imaging 22(11), 1395–1406 (2003)
2. Zheng, G., Rajamani, K.T., Nolte, L.-P.: Use of a dense point distribution model in a three-stage anatomical shape reconstruction from sparse information for computer assisted orthopaedic surgery: a preliminary study. In: Narayanan, P.J., Nayar, S.K., Shum, H.-Y. (eds.) ACCV 2006. LNCS, vol. 3852, pp. 52–60. Springer, Heidelberg (2006)
3. Zheng, G., Dong, X., Nolte, L.-P.: Robust and accurate reconstruction of patient-specific 3D surface models from sparse point sets: a sequential three-stage trimmed optimization approach. In: Yang, G.-Z., Jiang, T., Shen, D., Gu, L., Yang, J. (eds.) Proceedings of the 3rd International Workshop on Medical Imaging and Augmented Reality (MIAR). LNCS, vol. 4091, pp. 68–75. Springer, Heidelberg (2006)
4. Zheng, G., Nolte, L.-P.: Surface reconstruction of bone from X-ray images and point distribution model incorporating a novel method for 2D-3D correspondence. In: Proceedings of the 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR 2006) vol. 2, pp. 2237–2244 (2006)

5. Zheng, G., Gonzalez Ballester, M.A., Styner, M., Nolte, L.-P.: Reconstruction of patient-specific 3D bone surface from 2D calibrated fluoroscopic images and point distribution model. In: Larsen, R., Nielsen, M., Sporring, J. (eds.) MICCAI 2006. LNCS, vol. 4190, pp. 25–32. Springer, Heidelberg (2006)
6. Dryden, I.L., Mardia, K.V.: Statistical Shape Analysis. John Wiley and Sons, New York (1998)
7. Kendall, D.: A survey of the statistical theory of shape. Statistical Science 4(2), 87–99 (1989)
8. Small, C.: The statistical Theory of Shape. Springer, Heidelberg (1996)
9. Turk, M., Pentland, A.: Eigenfaces for recognition. Journal of Cognitive Neuroscience 3(1), 71–86 (1991)
10. Cootes, T.F., Taylor, C.J., Cooper, D.H., Graham, J.: Active shape models – their training and application. Computer Vision and Image Understanding 61(1), 38–59 (1995)
11. Corouge, I., Hellier, P., Gibaud, B., Barillot, C.: Interindividual functional mapping: a nonlinear local approach. Neuroimage 19, 1337–1348 (2003)
12. Fleute, M., Lavallée, S.: Building a complete surface model from sparse data using statistical shape models: application to computer assisted knee surgery system. In: Wells, W.M., Colchester, A.C.F., Delp, S.L. (eds.) MICCAI 1998. LNCS, vol. 1496, pp. 879–887. Springer, Berlin (1998)
13. Fleute, M., Lavallée, S., Julliard, R.: Incorporating a statistically based shape model into a system for computer-assisted anterior cruciate ligament surgery. Medical Image Analysis 3(3), 209–222 (1999)
14. Rajamani, K.T., Styner, M., Joshi, S.C.: Bone model morphing for enhanced surgical visualization. In: Proceedings of the 2004 IEEE International Symposium on Biomedical Imaging (ISBI): From Nano to Macro, pp. 1255–1258 (2004)
15. Rajamani, K.T., Gonzalez Ballester, M.A., Nolte, L.-P., Styner, M.: A novel and stable approach to anatomical structure morphing for enhanced intraoperative 3D visualization. In: Galloway Jr, R.L., Cleary, K.R. (eds): Proceedings of the SPIE Medical Imaging: Visualization, Image-guided Procedures, and Display. vol. 5744, pp. 718–725 (2005)
16. Fleute, M., Lavallée, S.: Nonrigid 3-D/2-D registration of images using statistical models. In: Taylor, C., Colchester, A.C.F. (eds.) Medical Image Computing and Computer-Assisted Intervention – MICCAI'99. LNCS, vol. 1679, pp. 138–147. Springer, Heidelberg (1999)
17. Yao, J., Taylor, R.H.: Assessing accuracy factors in deformable 2D/3D medical image registration using a statistical pelvis model. In: Proceedings of the 9th IEEE International Conference on Computer Vision (ICCV 2003), vol. 2, pp. 1329–1334. IEEE Computer Society (2003)
18. Lamecker, H., Wenckebach, T.H., Hege, H.-C.: Atlas-based 3D-shape reconstruction from X-ray images. In: Proceedings of the 18th International Conference on Pattern Recognition (ICPR 2006), vol. 1, pp. 371–374 (2006)
19. Benameur, S., Mignotte, M., Parent, S., Labelle, H., Skalli, W., de Guise, J.A.: 3D/2D registration and segmentation of scoliotic vertebrae using statistical models. Computerized Medical Imaging and Graphics 27, 321–337 (2003)
20. 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 Transactions on Biomedical Engineering 52(12), 2041–2057 (2005)
21. Chan, C.S.K., Edwards, P.J., Hawkes, D.J.: Integration of ultrasound-based registration with statistical shape models for computer-assisted orthopaedic surgery. In: Sonka, M., Fitzpatrick, J.M. (eds.): Proceedings of SPIE Medical Imaging 2003: Image Processing, vol. 5032, pp. 414–424 (2003)

22. Chan, C.S.K., Barratt, D.C., Edwards, P.J., Penney, G.P., Slomczykowski, M., Carter, T.J., Hawkes, D.J.: Cadaver validation of the use of ultrasound for 3D model instantiation of bony anatomy in image guided orthopaedic surgery. In: Barillot, C., Haynor, D.R., Hellier, P. (eds.) MICCAI 2004. Part II, LNCS, vol. 3217, pp. 397–404. Springer, Heidelberg (2004)
23. Talib, H., Rajamani, K.T., Kowal, J., Nolte, L.-P., Styner, M., Gonzalez Ballester, M.A.: A comparison study assessing the feasibility of ultrasound-initialized deformable bone models. Computer Aided Surgery 10(5/6), 293–299 (2005)
24. Talib, H., Zheng, G., Rajamani, K.T., Zhang, X., Styner, M., Gonzalez Ballester, M.A.: Feasibility of 3D ultrasound-initialized deformable bone-modeling. In: Langlotz, F., Ellis, R., Davis, B.L. (eds.) Proceedings of CAOS 2006, pp. 519–522 (2006)
25. Yao, J., Taylor, R.H.: Tetrahedral mesh modeling of density data for anatomical atlases and intensity-based registration. In: Delp, S.L., DiGoia, A.M., Jaramaz, B. (eds.) MICCAI 2000. LNCS, vol. 1935, pp. 531–540. Springer, Berlin (2000)
26. Blanz, V., Vetter, T.: A morphable model for the synthesis of 3D faces. In: Proceedings of the 26th Annual Conference on Computer Graphics, SIGGRAPH'99, pp. 187–194 (1999)
27. Zheng, G.: A novel 3D/2D correspondence building method for anatomy-based registration. In: Pluim, J.P., Likar, B., Gerritsen, F.A. (eds.) WBIR 2006. LNCS, vol. 4057, pp. 75–83. Springer, Heidelberg (2006)
28. Styner, M., Rajamani, K.T., Nolte, L.-P., Zsemlye, G., Székely, G., Taylor, C.J., Davis, R.H.: Evaluation of 3D correspondence methods for modeling building. In: Taylor, C.J., Noble, J.A. (eds.) IPMI 2003. LNCS, vol. 2732, pp. 63–75. Springer, Heidelberg (2003)
29. Brechbuehler, C., Gerig, G., Kuebler, O.: Parameterization of Closed Surfaces for 3D Shape Description. Comput Vision and Image Under 61, 154–170 (1995)
30. Davies, R.H., Twining, C.H., et al.: 3D statistical shape models using direct optimization of description length. In: Heyden, A., Sparr, G., Nielsen, M., Johansen, P. (eds.) ECCV 2002. LNCS, vol. 2352, pp. 3–20. Springer, Heidelberg (2002)
31. Loop, C.T.: Smooth subdivision surfaces based on triangles. M.S. Thesis, Department of Mathematics, University of Utah (August 1987)
32. Besl, P., McKay, N.D.: A method for registration of 3D shapes. IEEE Transaction on Pattern Analysis and Machine Intelligence 14(2), 239–256 (1992)
33. Bookstein, F.: Principal warps: thin-plate splines and the decomposition of deformations. IEEE Transaction on Pattern Analysis and Machine Intelligence 11(6), 567–585 (1989)
34. Moreland, J.R.: Primary Total Hip Arthroplasty. In: Chapman, M.W. (ed.) Operative Orthopaedics, 1st edn., vol. 1, pp. 679–693. JB Lippincott, Philadelphia, PA (1988)