3D Model-based Reconstruction of the Proximal Femur from Low-dose Biplanar X-Ray Images

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The 3D modeling of the proximal femur is a valuable diagnostic tool for orthopedic surgery planning such as total hip replacement and intertrochanteric osteotomy. The use of computed tomography is the most prominent modality to visualize bones both in terms of resolution as well as bone/tissue separation. Towards reducing the impact of radiation to the patient, low-dose X-ray imaging systems have been introduced while still providing partial views with rather low signal-to-noise ratio. Our work lies within this scope using the low dose EOS imaging system $(BiospaceMed^{TM})$[1] which is an alternative modality producing simultaneous biplanar X-ray images in an upright position. In this paper, we focus on automating the 3D proximal femur reconstruction from simultaneously acquired 2D views. A deformable model represented by triangulated mesh surfaces extends to a linear sub-space describing the variations across individuals. Principal component analysis (PCA) is used to describe the different modes of variation with a restricted number of parameters [1].

$$\widehat{S}(\mathbf{R},\mathbf{D}) = \overline{S}(\mathbf{R}) + \sum_{i=1}^{L} w_i V_i \quad (1)$$

$\overline{S}$ is the mean shape. $\mathbf{R}$ is a vector describing the rigid parameters. $\mathbf{D} = \{w_i\}_{i=1}^{L}$ are the shape parameters and $\{V_i\}_{i=1}^{L}$ are the eigenvectors. Segmentation consists of inferring a global deformation of 3D model followed by a local adaption based on the most prominent combination of the sub-space parameters. The basis of which relies on the minimization of a cost function based on the biplanar projection of this model. To this end, we employ an active region model[5] that aims at optimizing the 3D model parameters such that the projection of the surface is attracted to edge potentials, while creating an optimal partition between the bone class and the surrounding structures. The functional is the convex combination of the geodesic active contours and geodesic active regions:

$$E_{GAR}(C_i(\mathbf{R},\mathbf{D})) = \alpha E_C(C_i(\mathbf{R},\mathbf{D})) + (1-\alpha) E_R(C_i(\mathbf{R},\mathbf{D})), \quad (2)$$

where C is the projected silhouette contours and α is a weighting parameter. The active contours term reaches its minimum when the curve C falls along strong edges in the image, defining thus implicit distance maps defined as:

$$E_C(C_i(\mathbf{R},\mathbf{D})) = \oint_{C_i} g(C_i(s))ds, g(I) = \frac{1}{1+|\nabla I|}. \quad (3)$$

$$E_R(C_i(\mathbf{R},\mathbf{D})) = -\int\int_R log(p_R(I_i(u,v)))dudv. \quad (4)$$

The geodesic active regions part is a log-likelihood objective function which aims to encapsulate femur-like pixels within the projected silhouette of the 3D model while excluding background-like and other structure pixels: The global parameters of the model and the local ones are optimized through a gradient-free approach [4] that allows to overcome the inverse projection of the gradient from the 2D images to the 3D space.

$$\mathbf{R},\mathbf{D} = \underset{\mathbf{R},\mathbf{D}}{\operatorname{argmin}}\, E_{GAR}(C_1(\mathbf{R},\mathbf{D})) + E_{GAR}(C_2(\mathbf{R},\mathbf{D})). \quad (5)$$

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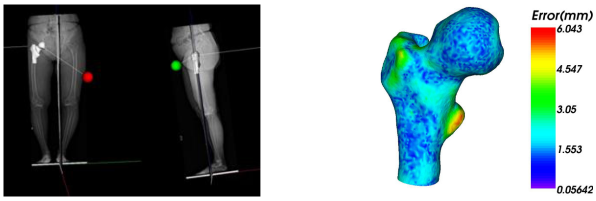

(a) (b)

Figure 1: (a) The first two eigenmodes of variation of the model and (b) the geometrical setup of the EOS system.

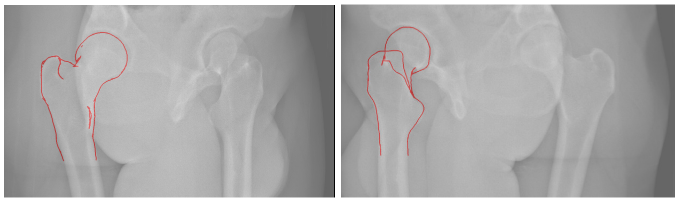

Figure 2: 2D segmentation results.

The resulting automatic one-stage framework does not require any user interaction to define 2D contours on the X-ray images in order to match the ASM model to a segmented silhouette. Note that prior work proposed by [2] require manual interaction to determine 2D contours which is not practical in an inter-operative context.

Promising results demonstrate the potentials of our method. Experiments were performed on both dry femurs and real clinical cases. We compared our results to those obtained by the gold standard CT segmented models as well as a method based on 2D manual segmentations[3]. In order to estimate the error between the method and the ground truth, we compute the DICE coefficients and statistics anchored on point-to-surface distances as well as estimating the most important femur specific clinical parameters.

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