3D Reconstruction Method of the Proximal Femur and Shape Correction

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Abstract—The aim of this work is to present a 3D reconstruction method of the proximal femur shape using contours identification from pairs of 2D X-ray radiographs without any prior acknowledge. 3D personalized model was reconstructed following a processing chain of seven different steps. After localization of the 2D contours on the images and the matching points of these contours, a 3D contour is generated using an algorithm based on a mathematical model. Thus, with a reduced number of pairs of images, we reconstruct a 3D points cloud, which enables obtaining a closed 3D surface. The accuracy of our approach was evaluated by comparing the reconstruction result with the 3D CT-scan reconstruction of cadaveric proximal femur. The estimated error shows that it is possible to rebuild the proximal femur shape from a limited number of radiographs.

Keywords—3D reconstruction, Proximal Femur, 2D Matching, 3D/3D Rigid Registration, Mesh.

I. INTRODUCTION

Three dimensional patient bone models provide an interesting analysis tool for the diagnosis and the follow-up of many bone diseases. The 3D bone models play also an important role in pre-operative surgery planning and improved guidance during surgery, modeling and simulation.

Accurate 3D anatomical models can be achieved using the direct 3D imaging modalities such as Computed Tomography (CT-Scan). However, the use of such imaging is restricted to minor specific procedures; due to the radiation risk, cost and availability [1]. Thus, the diagnosis and planning of many interventions still rely on two dimensional radiographic images, where the surgeon has to mentally visualize the 3D anatomy of interest. A direct 3D imaging must be developed, as an alternative to current 2D radiographs, in order to assist the clinicians on their medical tasks [1]. However, reconstructing a 3D bone shape from a restricted number of 2D X-ray images is a challenging task, especially when reconstructing a patient bone specific surface model. Moreover, for surgical application, high accuracy reconstruction is required. The error of reconstruction has to be in the range of surgical usability [2].

Literature on pre-operative reconstruction of bone models based on information collected through 2D imaging modalities can be divided into two groups. The methods of the first group use only 2D images for 3D model reconstruction [3]. The second group contains methods based on a prior knowledge of the 3D anatomical structure in addition to two or three 2D images [1]. Most of the studies require prior knowledge of the 3D anatomy model to compensate the lack of information from the 2D images [1].

This information can be provided by the integration of a generic geometrical surface of the considered bone structure [4], [5], or by Statistical Shape Models [2], [6], [7].

The aim of this study is to propose an approach for 3D proximal femur surface reconstruction using pseudo stereo matching and 3D points from a gold standard to reduce the lack of information. Only, a projective model and a limited number of 2D X-ray images taken from different orientations are employed for this purpose. Our method performs two main stages. In the first stage, two successive projections are used to compute the coordinates of a 3D contour. After extracting the contour of the proximal femur on the 2D X-ray images, the matching process is performed. The matching between the points of two contours is performed with the 2D Euclidian spatial distance. The estimated point pairs are then used to compute a set of 3D points. In the second stage, a reference model is used to extract points and inject them into the points cloud reconstructed to densify it and composite the lack of information, in order to improve the accuracy of the reconstructed 3D surface. To assess the accuracy of the proposed shape reconstruction framework, the results are compared to real 3D CT scan data. Three cadaver proximal femurs were used as the anatomy of interest throughout this study.

The paper is organized as follow: Section II presents the data and the material, followed by the method section. Section IV describes the shape correction method. Section V presents the different results. The paper is concluded in the last section.

II. MATERIAL

Using few X-ray image projections, the goal is to extract 3D information and establish the 3D shape of the femur. For this purpose, three cadaveric proximal femurs (F1, F2 and F3) were completely scanned using a CT scanner. This modality of imaging provides both the projections and the resulting 3D volume. X-Ray tomographic images were obtained using a high quality Computed Tomography (CT) scanner (cXplore CT120). The specimen was imaged with an isotropic pixel size of 50 μm. The specimen was placed between the x-ray source and the sensor in rotation, 360 radiographs (projections) were acquired on 360 degrees with an interval of one degree between two successive projections. The 3D volume was reconstructed using an implementation based on Feldkamps cone beam reconstruction algorithm [8]. Examples of the ex vivo proximal femur radiographs are shown in Fig. 1. The 3D models of the reconstructed proximal femurs are shown in Fig. 2. These models have been utilized as ground truth to compare the performance of our proposed algorithm.
Fig. 1. X-ray images of the *in vivo* proximal femur F1 at different projection angles.

<table>
<thead>
<tr>
<th>3D ground truth of the proximal femur F1</th>
<th>3D ground truth of the proximal femur F2</th>
<th>3D ground truth of the proximal femur F3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Front view</td>
<td>Front view</td>
<td>Front view</td>
</tr>
<tr>
<td></td>
<td>Back view</td>
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</tr>
</tbody>
</table>

Fig. 2. 3D ground truth of the three proximal femurs used for the test and reconstructed from 360 radiographs using X-ray tomography imaging.

**III. PROCESSING CHAIN**

Figure 3 shows the processing flow chart and the different steps of the developed method. Next sections describe each step of this chain.

**A. Projection model**

Figure 4 shows the used model for the acquiring process. The proximal femur is placed between the X-ray source and the sensor in rotation by an angle $\alpha$ after each acquisition. The pairs of points (P1, O1) and (P2, O2) represent the projection of a point P of the object and the projection of the center of rotation O on the sensor before and after rotation, respectively. From the coordinates of the points P1 and P2 and using a mathematical model, we determine the 3D coordinates of the point P. This model is detailed in Section III. D.

Since we are using a minimum of radiographic images, we are interested in the impact of the choice of the angle between two radiographs as well as the influence of the angle between two pairs of radiographs on the quality and the accuracy of the 3D reconstructed shape. To do so, the angle $\alpha$, between two images of the same pair was fixed to 4 degrees and the angle $\beta$ between the pairs was set to different values 10, 20, 30, 45 and 60 degrees.

For each angle $\beta$, the error between the 3D reconstructed shape and the ground truth was estimated and the optimal orientation $\beta_0$ giving the minimum error was retained. Keeping the angle $\beta_0$, the next step consists in varying the angle $\alpha$ from 4 to 32 degrees by power of 2, in order to get the best combination ($\alpha_0$, $\beta_0$) that enables reconstructing the 3D desired shape close to the ground truth. Fig. 5 illustrates the scheme of different pairs of X-ray projections separated by the angles $\alpha$ and $\beta$.

Fig. 3. The proposed processing flow chart.

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There exists several works for contours matching [11], [12], [13]. For this work, the matching between the points of two contours is performed by computing three different distances, the City-block, the Chess board and the Euclidian 2D spatial distance. The distance which gave the minimum error after the 3D reconstruction was retained.

Let us denote the coordinates of the detected edge pixels in image 1 (red edge, Fig. 7) as \( I_1 = f(x^i, y^i), i = 0, 1, ..., M-1 \) and the detected edge pixels in image 2 (green edge, Fig. 7) as \( I_2 = f(x^j, y^j), j = 0, 1, ..., N-1 \), where \( M \) and \( N \) are the number of the edge points detected in image 1 and in image 2, respectively. The matching process consists in finding for each point in the set \( I_1 \), the closest one in \( I_2 \), by computing the City-block \( d_1 \) as (3), the Chess-board \( d_2 \) as (4) and the Euclidean distance \( d_3 \) as (5).

\[
\begin{align*}
  d_1(x, y) & = |x^i - x^j| + |y^i - y^j|, \quad (3) \\
  d_2(x, y) & = \max \left( |x^i - x^j|, |y^i - y^j| \right), \quad (4) \\
  d_3(x, y) & = \sqrt{(x^i - x^j)^2 + (y^i - y^j)^2}. \quad (5)
\end{align*}
\]

After comparing the results obtained with the three distances, we found that the Euclidean distance gives the best results and thus is retained for the experiments of this study.

Since we are using binary images, the correspondence of the contour 1 towards the contour 2 is not symmetric and may give different results if contour 2 is used towards contour 1, therefore, the 3D reconstruction result may be different. Here, we will discuss this issue and study its influence on the 3D reconstructed models. We compared the results of the following four configurations:

- **Configuration 1**: Contour 1 towards contour 2.
- **Configuration 2**: Contour 2 towards contour 1.
- **Configuration 3**: the intersection between the results of configurations 1 and 2. The goal is to keep the pairs of pixels that are common to both configurations.
- **Configuration 4**: the union of the results of the configurations 1 and 2. We keep the maximum pixel pairs.

The four configurations are shown in Fig. 8.
The obtained results showed that the matching contours of the configuration 1 provides a minimum error, hence we use this configuration for the experiments. The estimated point pairs are then used to set up a set of 3D points.

D. Generation of the 3D points cloud

Taking the diagram of the Fig. 4, the bone is set between the source and the sensor, the Y-coordinate (height) is fixed to a known position, the source and the sensor are rotated around the object along the Y axis. We consider the 2D reference, R(X, Z).

For the point P having as projected onto the sensor the pixel P1 with the coordinates (P1x, P1y), knowing the distance between the X-ray source (S1) and the sensor C1, and the distance between the bone and the source, using Thales' theorem, it is possible to calculate the Y coordinate of the point P (Fig. 9).

The formula to calculate the Y coordinate is defined as follows:

\[
\frac{O_{S_1}}{P_y} = \frac{Y}{Y_1} \Rightarrow Y = \frac{O_{S_1}}{P_y} \cdot P_y.
\]  

Once the Y coordinate found, the resolution of the system of the two obtained equations using the straight lines (S1P1) and (S2P2) (Fig. 4), is used to calculate two coordinates X and Z.

The first equation represents the straight line D1 (Fig. 4) connecting the X-rays source S1 to the point P1 which represents the projection of point P on the sensor before the rotation of the source-sensor system.

\[
Z = -O_{O_1} - O_{S_1} \times X + O_{S_1},
\]  

\( O_{O_1} \): is the distance between the bone and the sensor.
\( O_{S_1} \): is the distance between the bone and the X-ray source.
\( P_1x \): is the x coordinate of the projected point P on the sensor.

The second equation shows the same straight line D1 linking the X-ray source and the sensor through the point P after rotation of the source-sensor system by an angle \( \alpha \). As the object and source-sensor distance are fixed, the distances between, source-object and object-sensor are invariant. Thus, we have

\[
O_{O_1} = O_{O_2} \quad \text{and} \quad O_{S_1} = O_{S_2}. \tag{8}
\]

Thereby, we can write the equation of the second straight line D2 (Fig. 4) as follows:

\[
Z = -O_{O_1} \times \cos \alpha - P_1x \times \sin \alpha - O_{S_1} \times \cos \alpha \times \sin \alpha \times X + C.
\]  

\( \alpha \): is the distance between the bone and the sensor.
\( O_{O_1} \): is the distance between the bone and the X-ray source.
\( P_1x \): is the x coordinate of the projected point P on the sensor.

The solution \((X, Z)\) of the system of equations (7) and (9) is the coordinates of the point \( P \). Thus, for each pair of projections separated by an angle \( \alpha \), it is possible from the system of these equations to estimate the coordinates of a 3D contour. Using several pairs of images, a 3D points cloud is obtained.

E. 3D/3D rigid registration

Before the meshing step of the computed 3D points cloud, a rigid registration, with a 3D points cloud extracted from the ground truth, is applied. We used the Iterative Closest Point (ICP) algorithm [14], [15], [16] to align two clouds of points. The first step of the ICP algorithm is based on the search of pairs of nearest points between the two sets (reconstructed and ground truth). The second step includes the estimation of the optimal rigid transformation that aligns the two data sets. Then, in the last step, the rigid transformation is applied to the points of the reconstructed data. The procedure iteratively revises the transformations (translation, rotation) needed to minimize the distance between the points until convergence is achieved. Registering the 3D points cloud in the same environment enables estimating the error between the two surfaces.

F. Meshing

Next, comes the meshing and texture mapping of the computed 3D points cloud. This task was achieved using Meshlab [17] which is an advanced 3D software system for the processing and editing of unstructured 3D triangular meshes. Based on the normals of the points, we used the Poisson surface reconstruction algorithm proposed by Meshlab. Then, after texture mapping a 3D closed surface is obtained.

IV. Shape correction

With our approach, we have reconstructed the proximal femurs surfaces with good accuracy as shown in Table 1 and Fig. 11. However, a detailed analysis of the results shows that there is a part of residual error of the upper part of the femoral neck on the side of the greater trochanter, due to occlusion effect leading to bad edge detection and matching at the cavity between the femoral neck and the greater trochanter, which is the most difficult area to rebuild. To reduce this error and improve the reconstructed shape, we introduced a new technique to densify the reconstructed points cloud and overcome the lack of information in some areas.

In this method, we used points extracted from a gold standard cloud to densify and rebuild the points cloud (Fig. 10). We calculate the 3D Euclidean distance between the points of the gold standard and those of the rebuild cloud.
The Euclidean distance is used as a criterion to select only relevant points, i.e. points away from existing ones. The threshold depends on the percentage of points that we want to insert from the reference could in the surface to be reconstructed. This percentage is calculated from the total 3D cloud surface points already rebuilt. We considered several points’ percentages: 5 %, 10 %, 15% and 20%.

To validate our approach, we used the volume CT-Scan of the proximal femur F1 as reference volume to rebuild the proximal femur F2 and vice versa, the CT-Scan of the proximal femur F2 as a reference volume to reconstruct the proximal femur F1. The results obtained for the two proximal femurs F1 and F2 are shown in Table 2.

V. RESULTS

Figure 11 presents the estimated errors in comparison to the ground truth. These errors were evaluated using the Metro tool for measuring error on simplified surfaces [18]. The red and blue colors in the 3D reconstructed shapes represent respectively the high and the low error values.

Table 1 presents the maximum error, average error and RMS obtained for the 3D reconstruction of the three proximal femurs. Fig. 11 shows a visual example of the obtained 3D surfaces and the reconstruction errors for the three proximal femurs.

<table>
<thead>
<tr>
<th>Inserted points</th>
<th>Maximum (mm)</th>
<th>Mean (mm)</th>
<th>RMS (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>F1</td>
<td>9.241</td>
<td>0.906</td>
<td>1.359</td>
</tr>
<tr>
<td>F2</td>
<td>8.775</td>
<td>0.891</td>
<td>1.301</td>
</tr>
<tr>
<td>5%</td>
<td>8.654</td>
<td>0.933</td>
<td>1.207</td>
</tr>
<tr>
<td>10%</td>
<td>8.660</td>
<td>0.969</td>
<td>1.223</td>
</tr>
<tr>
<td>15%</td>
<td>8.641</td>
<td>0.906</td>
<td>1.359</td>
</tr>
<tr>
<td>20%</td>
<td>8.630</td>
<td>0.933</td>
<td>1.207</td>
</tr>
</tbody>
</table>

The results show that more the number of inserted points is important, better the reconstruction is. These results are consistent with our expectations. The maximum error decreases substantially (Fig.12 and Fig. 13), for example, the great trochanter is better reconstructed with more information. However, beyond the 15% of injected points, the average and the RMS errors increased slightly because the other parts of the proximal femur tend to take the shape of the reference volume. This demonstrates the importance of the combination of the two approaches of stereo reconstruction and shape constraint by adding a percentage of points from the reference model.

![Fig. 12. Maximum errors, average and RMS errors obtained with the different percentages of inserted points for the proximal femur F1.](image)

![Fig. 13. Maximum errors, average and RMS errors obtained with the different percentages of inserted points for the proximal femur F2.](image)
CONCLUSION

This work shows that it is possible to reconstruct the 3D surface of the proximal femur from relatively small number of X-ray projections with an average error of 0.89 mm and an RMS of 1.37 mm. The proposed reconstruction scheme combines X-ray stereo model and shape constraint. The accuracy of the reconstructed shape is improved by incorporating 3D points extracted from a reference model obtained from CT-Scan images. Our proposed approach for the 3D surface reconstruction of the proximal femur seems to be an interesting and promising technique.

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