Automatic Motion Estimation and Compensation Framework for Weight-bearing C-arm CT scans using Fiducial Markers

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Abstract— **Cone-beam CT systems are widely used because of their high flexibility with respect to patient position and scan trajectory. In the last years, C-arm CT systems have been used to acquire images in weight-bearing conditions in order to expose, e.g. the knee joint under realistic loads. Straight standing or squatting patient positions lead to involuntary patient motion during the acquisition. In this paper, a fully-automatic motion estimation and compensation framework to mitigate knee-joint motion during weight-bearing C-arm scans is presented. Our framework consists of three major steps: marker detection with outlier removal, motion estimation and correction, and marker removal. The marker detection is based on an initial estimate of the marker position extracted from the motion-blurred filtered backprojection (FDK) reconstruction and on the fast radial symmetry transformed (FRST) 2-D projection images. The motion is estimated by the alignment of the forward projected 3-D initial marker positions with the actual detected 2-D marker positions. The motion is then corrected in the filtered backprojection step. Finally, the detected markers are removed in the 2-D projection images by simple interpolation. The framework was evaluated on three C-arm CT datasets from one volunteer in a straight standing, moderate squatted and deep squatted position. All 3-D reconstructions show a large improvement in image quality compared to the non-corrected 3-D reconstructions.**

Keywords— **Image Reconstruction, Knee-Joint Imaging, Motion Estimation, Fiducial Markers, Cone-beam CT**

I. Introduction

Recently, C-arm CT systems have been used to acquire three-dimensional images of knee-joints under weight-bearing conditions, which expose the knee to realistic loads. In comparison to a conventional CT or MRI scan in supine position, the knee kinematics and the stress on the cartilage are more realistic. C-arm CT acquisitions collect numerous high-resolution 2-D images over a pre-defined angular range for a three-dimensional reconstruction. Unfortunately, the time necessary to acquire a sufficient number of 2-D images for 3-D reconstruction can be up to several seconds. At this time scale, involuntary patient motion, especially in a squatting position, is unavoidable and can cause severe artifacts in the 3-D images. These artifacts can obscure important information and substantially decrease the clinical utility of the CBCT images.

In the literature, several papers emply data consistency conditions for motion estimation [1, 2, 3, 4]. Up to now, these techniques have been successfully applied to simulated phantom data, but have not yet been applied to clinical data acquired with a C-arm system due to the limited scan range of about 200° and the cone-beam geometry.

Numerous publications exploit external fiducials for motion estimation because they can be directly tracked in the 2-D projection images. Fiducial marker-based methods are advantageous because they do not rely on any trajectory assumptions and they do not require additional radiation or a prior CT scan. The idea of motion correction using fiducial marker detection has been already widely used in medical imaging [5, 6, 7, 8], although to date the approach has not been implemented on a real clinical C-arm CT system. In comparison to Choi et al. [7], we present a fully-automatic global motion estimation and compensation framework for CBCT knee scans under weight-bearing conditions using fiducial markers.

II. Methods

A. 2-D Fiducial Marker Detection

First, the fiducial markers attached to the patients knee need to be detected in the individual 2-D projection images. In our framework we use an automatic marker detection approach, presented by Berger et al. [9]. In order to remove larger objects than the markers from the projection images, a morphological top-hat filter [10], followed by a Sobel filter to enhance the remaining structures is used. Next, the fast radial symmetry transform (FRST) [11] is applied to the pre-processed 2-D images to detect the initial marker positions. Therefore, a Gaussian filter is applied to the FRST images and the 2-D candidate points are backprojected to get a distinct outcome for each 3-D marker position. A binarisation step is performed utilizing the maximum entropy method [12]. Next, a 3-D connected component analysis is applied to identify the centroids of the marker positions in 3-D. The 3-D reference markers can be forward projected onto each projection image with the help of the pre-calibrated projection matrices, $\boldsymbol{P}_j \in \mathbb{R}^{3\times 4}$ for each projection image $j \in \{1,\ldots,N\}$, with N the number of projection images,yielding the 2-D reference points $\boldsymbol{r}'_{i,j}$, for each marker $i \in \{1,\ldots,B\}$, with B denoting the number of markers. As a next step, a set of 2-D candidate points $\boldsymbol{m}_{i,j}$ are extracted from the initial FRST images, using a heuristically determined threshold and a 2-D connected-components analysis. These candidate points are then assigned to the closest 2-D reference points, essentially solving the correspondence problem. The 3-D marker positions can be updated by the newly assigned candidate points and the whole detection can be performed iteratively.

B. Outlier Removal

The detection of candidate points in the 2-D FRST processed projection images can lead to incorrect marker positions,which typically occurs when markers are clustered in the projection images. In order to increase robustness, 2-D outliers are removed before the motion estimation step. In order to detect the outlier, the 3-D motion trajectory of each marker is projected on the uz- and vz-plane, with u denoting the axis for the width and v the axis for the height of each projection image, and z the number of projections. For each 2-D marker trajectory a cubic smoothing spline is fitted to the original 2-D curve. If the distance of the original marker position to the new marker position is larger than a certain threshold, the point is considered an outlier. The smoothed trajectory is only used for our outlier detection. The original motion trajectory is used for motion correction excluding the identified outliers.

C. 2-D/3-D Rigid Motion Estimation

For the estimation of the intra-scan motion based on the detected marker positions, the approach used by Choi et al. [13, 7] is adapted. The algorithm estimates a 3-D rigid transformation for each projection image j, by fitting the forward projection of the 3-D reference marker position to the actual 2-D detected candidate points. Each transformation matrix $\boldsymbol{M}_j \in \mathbb{R}^{4\times 4}$, with

$$\boldsymbol{M}_j = \boldsymbol{T}_j(t_{x,j}, t_{y,j}, t_{z,j}) \cdot \boldsymbol{R}_z(\gamma_j) \cdot \boldsymbol{R}_x(\alpha_j) \cdot \boldsymbol{R}_y(\beta_j), \qquad (1)$$

has six degrees of freedom, where $\boldsymbol{T}_j \in \mathbb{R}^{4\times 4}$ is the translation and $\boldsymbol{R} \in \mathbb{R}^{4\times 4}$ are the rotation matrices. In this paper, the unknown parameters are estimated by an interior-point optimizer [14], with the given objective function:

$$\underset{t_{x,j}, t_{y,j}, t_{z,j}, \gamma_j, \alpha_j, \beta_j}{\arg\min} \sum_{j=1}^{N} \sum_{i=1}^{B} ||\boldsymbol{r}'_{i,j} - \boldsymbol{m}_{i,j}||_2^2. \qquad (2)$$

In order to perform a motion-compensated reconstruction, each $\boldsymbol{M}_j$ rigid transformation matrix is used to compute a new calibration matrix $\boldsymbol{P}_j^{new}$

$$\boldsymbol{P}_j^{new} = \boldsymbol{P}_j \cdot \boldsymbol{M}_j, \qquad (3)$$

with $\boldsymbol{P}_j$ denoting the pre-calibrated projection matrix for projection image j.

III. Results

A. Experiment

The authors use images of one healthy volunteer standing and squatting at several knee flexion angles. These images were acquired under an IRB approved protocol. In order to identify the involuntary motion of the lower body, sixteen 1-mm-diameter tantalum fiducial markers from Baltec™ were attached around both knees. The volunteer was scanned using an Axiom Artis dTA system (Siemens AG, Healthcare Sector, Forchheim, Germany). A CBCT weight-bearing scan acquisition protocol was used, with the following scanning parameters: the scan time was 10 s, and 248 images were acquired at 30 f/s, and with an angular increment of 0.4° during the C-arm sweep. The isotropic pixel resolution was 0.308 mm/pixel (0.20mm at isocenter) and the detector size was 960 × 1240 pixels. Image reconstruction was performed with a Shepp-Logan ramp filter with roll-off factor on an image volume of $(25.6\ \text{cm})^3$ distributed on a 512^3 voxel grid using the CONRAD framework [15]. Three different scans with different knee flexion angles were performed: (1) standing straight 0°, (2) moderate squat 35°, and (3) deep squat 60°.

B. Visual Inspection

The motion corrupted and the motion corrected 3-D reconstructions are shown in Figure 1. The top row shows an axial slice of the femur and patella for the three different scans (Figure 1a-1e). The motion artifacts increase with the flexion angle from $0° - 60°$. A clear improvement is visible in the motion-corrected reconstructions (Figure 1b-1f). This also applies to the axial slices showing tibia and femur (Figures 1c-1h).

(a) w/o correction (1) | (b) with correction (1) | (c) w/o correction (1) | (d) with correction (1)

(e) w/o correction (2) | (f) with correction (2) | (g) w/o correction (2) | (h) with correction (2)

(i) w/o correction (3) | (j) with correction (3) | (k) w/o correction (3) | (l) with correction (3)

Fig. 1: Three-dimensional reconstructions of the volunteer in three (1),(2), and (3) different standing positions. The first column shows motion corrupted reconstructions of the femur and patella, . The corresponding motion corrected reconstructions are shown in the second column. The third column shows an axial slice of the motion corrupted reconstructions of tibia and fibula. The according motion corrected reconstructions are shown in the last column.

C. *Quantitative Results*

In Table 1, the minimum, maximum, mean, and median number of markers detected on each scan are listed. Due to the changinh squatting position, the number of markers visible over the whole scan varies. On average, 16 tantalum markers could be observed. The improvement gained via motion correction is measured with the 2-D Euclidean distance between the forward projected 3-D markers and the corresponding 2-D detected markers. In Table 2, the mean error ε before and $\varepsilon_{\text{trans}}$ after transformation with and without outlier removal is listed.

Table 1: The minimum, maximum, mean, and standard deviation, and median number of markers detected on the three weight-bearing scans.

Dataset	Min	Max	Mean $\pm$ Std	Median
Standing straight	9	15	13.89 $\pm$ 1.04	14
Moderate squat	9	15	13.89 $\pm$ 1.04	14
Deep squat	11	16	15.58 $\pm$ 0.78	16

IV. Discussion

Weight-bearing CBCT scans with different knee flexion angles exhibit tremendous motion artifacts when the patient is not standing in a full upright position. In this paper, a complete automatic motion estimation and compensation framework is presented using fiducial markers attached to the pa-

Table 2: The mean error ε defines the error between the forward projected 3-D reference points and the detected 2-D candidate points on the FRST images and the mean error $\varepsilon_{\text{trans}}$ between the transformed forward projected 3-D reference points.

	No Outlier Detection	
Dataset	ε	$\varepsilon_{\text{trans}}$
Standing straight	2.53 ± 1.07	0.61 ± 0.20
Moderate squat	10.65 ± 5.97	1.29 ± 0.53
Deep squat	11.67 ± 7.96	2.33 ± 1.61
	Outlier Detection	
Dataset	ε	$\varepsilon_{\text{trans}}$
Standing straight	2.53 ± 1.07	0.60 ± 0.19
Moderate squat	10.64 ± 5.95	1.25 ± 0.38
Deep squat	11.65 ± 7.94	2.25 ± 1.34

tient's knees. The visual and the quantitative results of three different scans of one volunteer show immense image quality improvement. The motion correction method also recovers small structures as for example around the fibula. The automatic marker detection combined with the outlier detection works reliably on three datasets. However, in the lateral views when the knees completely overlap, the marker assignment may lead to false pairings between the forward projected 3-D reference marker and the actual 2-D detected marker. Most of these errors are detected as outliers in the outlier removal step.

V. Conclusion

In this paper, we presented a fully automatic motion estimation and compensation framework for weight-bearing knee data using a C-arm CT system utilizing fiducial markers. The resulting image quality is considerably better than standard FDK reconstructions with no motion correction. The application of the methods to three datasets with different squatting positions are promising and encourage further evaluation in a clinical environment.

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