Fusing Motion Estimates for CBCT Reconstruction

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***Abstract*—Involuntary patient motion decreases image quality of cone-beam CT acquisitions acquired under weight-bearing conditions. Thus, motion compensation is crucial for assessing knee cartilage health in the reconstructed images. Previous methods for motion compensation used externally attached fiducial markers and 3D/2D registration of prior scans to the projection data. Recently, the combination of cone-beam CT and range-imaging has received increasing attention, as it allows motion compensation based on 3D surface data. We recently proposed an Iterative Closest Point (ICP)-based method to compensate for motion by alignment of surface data. Despite promising results, motion estimates parallel to the rotation axis proved error prone. Yet, motion in this direction is usually estimated very well with projection domain methods, such as Amsterdam Shroud (AS).**

In this work, we investigate sensor fusion of ICP and AS based on particle filtering. The ICP motion estimates are improved with a motion surrogate signal obtained by the AS method.

Compared to the ICP-based approach, the proposed fusion yields superior motion estimation accuracy and reconstruction quality, improving the Structural Similarity from 0.96 to 0.99. Our preliminary results are promising and suggest a high potential of particle filter-based sensor fusion for motion compensation in cone-beam CT. Future work will investigate possibilities to derive fusion parameters automatically from improvements in image quality achieved with a particular estimate.

I. Introduction

NOVEL cone-beam CT (CBCT) image acquisition protocols facilitate imaging of the human knee joint under weight-bearing conditions [1], [2]. This enables the assessment of knee joint health under more realistic conditions. In these scans, the X-ray source and the detector rotate horizontally around the standing patient, who tends to show involuntary motion during the scan time of approximately ten seconds. This motion leads to inconsistencies in the acquired projection images, resulting in motion artifacts in the reconstructions that manifest as streaks, double edges, and blurring. In order to increase the diagnostic value of the reconstructions, motion estimation and compensation is indispensable.

One method to compensate for motion relies on fiducial markers placed on the patient's skin. These markers can be detected in the 2D projection images and afterwards aligned to a 3D reference position. However, attaching markers is time consuming and tedious, since overlapping markers in the projection images decrease the estimation accuracy. Another category of approaches are purely image-based and use prior knowledge [3], 2D/3D registration [4], [3], or autofocus [2].

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Recently, methods based on dense surface information acquired simultaneously to the CBCT have received increasing attention [5], [6]. In a first feasibility study [5], we registered point clouds using an Iterative Closest Point (ICP) algorithm. The results were promising, but also indicated that motion estimates parallel to the rotation axis are unreliable.

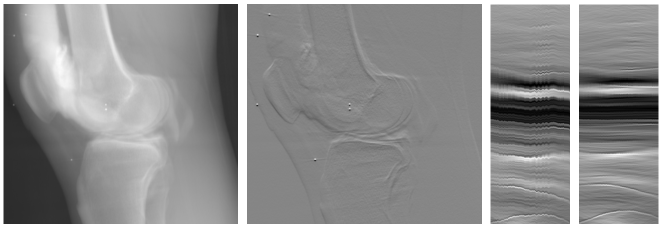
In this work, the ICP-based motion estimation method is extended and combined with the Amsterdam Shroud (AS) method [7]. This method was initially developed for extracting diaphragmatic motion. Despite good performance, it's applicability is limited to motion occurring parallel to the rotation axis. Here, we utilize a particle filter to fuse estimates from both approaches. Evaluation is performed qualitatively by comparing reconstructions visually and quantitatively by computing the Structural Similarity (SSIM).

II. Materials and Methods

Data: X-ray projections and point clouds are simulated on a segmented knee, extracted from a clinical high resolution supine reconstruction. The data was acquired on a clinical C-arm CT system (Artis Zeego, Siemens Healthcare GmbH, Erlangen, Germany). For each time point, an X-ray image and point cloud is simulated in the same motion state, which is real patient motion acquired with a motion capture system [5]. Other than the X-ray source, the depth camera does not rotate around the patient but is static. Motion is simulated to be 3D translation. Figure 1a shows an exemplary X-ray projection.

ICP-based Motion Estimation: Dense surface point clouds are registered to the first motion state using a point-to-surface ICP algorithm [5]. The registration yields 3D translations, representing object motion. Whilst the results are reliable in x (perpendicular to rotation axis) and y (depth) direction, the z direction, parallel to the rotation axis proved to be unreliable.

Motion Estimation using Amsterdam Shroud: The AS [7] algorithm has been developed to extract a breathing signal from a consecutive stack of projection images, resulting in a 1D signal corresponding to motion parallel to the rotation axis (z component). In a first step, the vertical image gradient is computed for each projection, see Figure 1b. Then, all 2D images are integrated horizontally and the resulting 1D signals are stacked next to each other, see Figure 1. Line shifts in vertical direction, are optimized such that the sum of squared distances between neighboring lines is minimal, see Figure 1d. In our application, cortical bone of the distal femur and the proximal tibia serve as orientation points as they yield large contributions to the AS signal. This is especially valuable, since this area is of particular interest for improvements in reconstruction quality.



(a) (b) (c) (d)

Fig. 1: (a) shows an exemplary projection image. (b) shows a gradient image. (c) and (d) show the shrouded image before and after optimization, respectively.

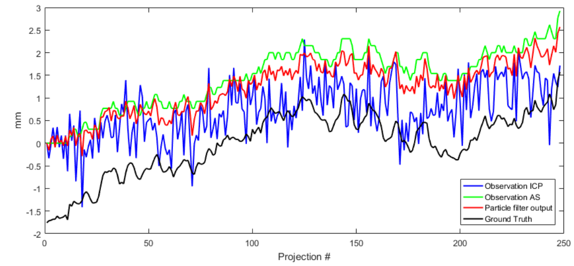
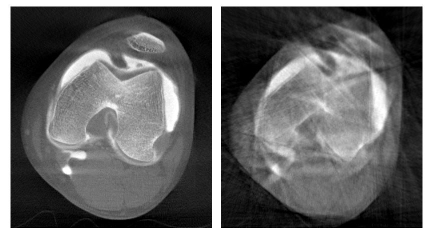
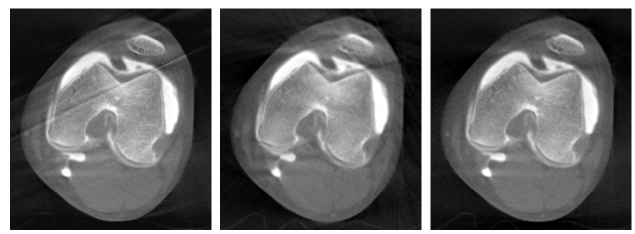


Fig. 2: Particle filter output for estimation shifts in z direction. Note that an offset is not relevant for reconstruction.



(a) Ground truth. (b) Motion corrupted.



(c) Marker-based [1]. (d) ICP-based [5]. (e) Proposed method.

Fig. 3: Reconstructed axial slices through the knee joint.

Particle Filter Motion Estimation: The two motion estimates in z direction of the ICP and the AS method are considered to be observations of the same true motion state with certain uncertainties. A particle filter is able to predict the optimal state of the estimation, given observations and their variances. We set these values empirically to $\sigma = 1\,\text{mm}$ for the signal of the AS algorithm and $\sigma = 5\,\text{mm}$ for the ICP-based output. Note that the shifts of the ICP-based method are estimated on the object surface, while the AS estimates motion in the isocenter of the object corresponding to scaled versions of vertical detector shifts.

Experiments: We use the real scanner geometry with 248 projection images over a rotation of 200°. Detector resolution is 1240×960 pixels with an isotropic pixel size of 0.308 mm. Volumes with a size of 512^3 and an isotropic voxel size of 0.5 mm are reconstructed. The processing, simulation, and reconstruction pipeline is implemented in the open-source framework CONRAD [8]. In order to compare the image quality of the results, the SSIM is computed. To this end, all reconstructions are registered to the motion free reference reconstruction. The estimated motion is incorporated in the projection matrices prior to reconstruction.

III. Results

In Figure 2, the ground truth, the ICP, the AS, and the particle filter signal of the z-direction is plotted. The noisy estimate of the ICP algorithm is substantially stabilized by the particle filter. Further, the offset in the estimation will effect the reconstruction to be shifted in the world coordinate space, but not the reconstruction quality. Therefore, we calculated the correlation coefficient between the ground truth and the ICP estimated signal and achieved an improvement from 0.59 to 0.94 using the particle filter.

In Figure 3, reconstruction results of the ground truth, the uncorrected, the marker-based, the ICP-based and the proposed method are shown. Severe motion artifacts are visible if no correction is applied. All other methods reduce the motion artifacts remarkably. Prominent streaks in the marker-based result appear due to overlapping markers in the projection images. Reconstructions obtained with the purely ICP-based method still exhibit slight streak artifacts that are notably reduced when the proposed method is used.

To quantify the performance, SSIM is shown in Table I. The results support the visual impression: all methods improve the image quality compared to the corrupted case. Further, the ICP-based results were improved from 0.96 to 0.99 when the proposed fusion is applied.

IV. Discussion and Conclusion

We present a sensor fusion framework to improve motion compensation performance in weight-bearing CBCT imaging of knees. Using a particle filter, we combine two inaccurate motion estimates obtained with an ICP-based and an AS-based method operating on depth and projection images, respectively. Currently, only 3D translation is investigated. Future work has to address the behavior of noise in the data. Moreover, practical issues such as calibration and synchronization have to be addressed when moving towards real data application [9]. Yet, this work constitutes the next step towards using dense surface data for estimation of patient motion.

TABLE I: SSIM of the reconstructed images.

Method	SSIM
Uncorrected	0.90
Marker-based [1]	0.98
ICP-based [5]	0.96
Proposed particle filter-based	0.99

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