Image-based Compensation for Involuntary Motion in Weight-bearing C-arm CBCT Scanning of Knees

Mathias Unberath, Jang-Hwan Choi, Martin Berger, Andreas Maier, Rebecca Fahrig

February, 24. 2015

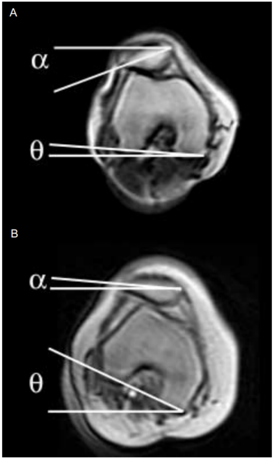
Pattern Recognition Lab, FAU Erlangen-Nürnberg
Radiological Sciences Lab, Stanford University

STANFORD SCHOOL OF MEDICINE
Stanford University Medical Center

SAOT erlangen graduate school in advanced optical technologies

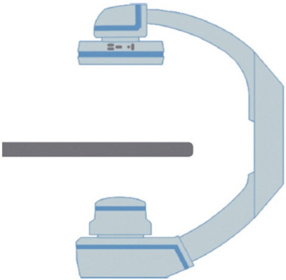
FAU FRIEDRICH-ALEXANDER UNIVERSITÄT ERLANGEN-NÜRNBERG
TECHNISCHE FAKULTÄT

Context



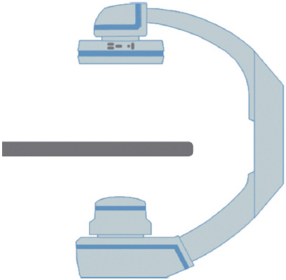
- Knee-joint kinematics change under strain
  - In particular: different flexion angles
  - → Weight-bearing imaging may be advantageous
- Enable weight-bearing acquisitions
  - → Dedicated CBCT scanners
  - → Existing systems
- C-arm CT scanners
  - → Horizontal trajectories
  - → Wide volumetric beam coverage

Context



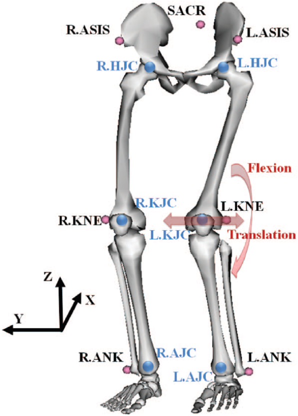
- Knee-joint kinematics change under strain
  - In particular: different flexion angles
  - → Weight-bearing imaging may be advantageous
- Enable weight-bearing acquisitions
  - → Dedicated CBCT scanners
  - → Existing systems
- C-arm CT scanners
  - → Horizontal trajectories
  - → Wide volumetric beam coverage

Context



- Knee-joint kinematics change under strain
  - In particular: different flexion angles
  - → Weight-bearing imaging may be advantageous
- Enable weight-bearing acquisitions
  - → Dedicated CBCT scanners
  - → Existing systems
- C-arm CT scanners
  - → Horizontal trajectories
  - → Wide volumetric beam coverage

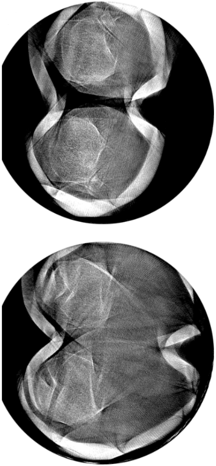
Context



- Weight-bearing acquisitions:
  → From standing upright through to deep squats (65° flexion)
- Involuntary knee motion during scans
  → Severe motion artifacts
- Previously: Use of fiducial markers Compensation in:
  - Reconstruction space
  - Projection space

Image-based compensation possible?

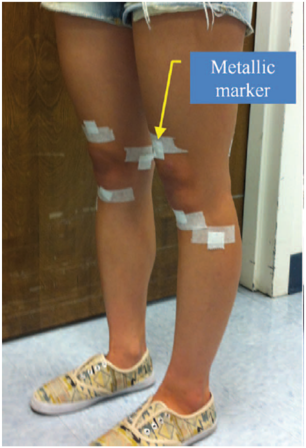
Context



- Weight-bearing acquisitions:
  - $\rightarrow$ From standing upright through to deep squats (65° flexion)
- Involuntary knee motion during scans
  - $\rightarrow$ Severe motion artifacts
- Previously: Use of fiducial markers
  Compensation in:
  - Reconstruction space
  - Projection space

Image-based compensation possible?

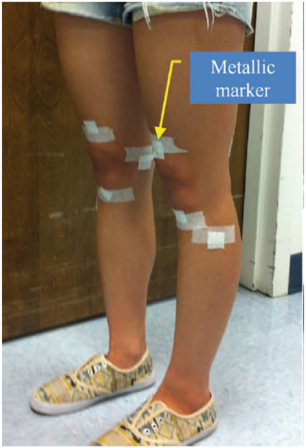
Context



- Weight-bearing acquisitions:
  → From standing upright through to deep squats (65° flexion)
- Involuntary knee motion during scans
  → Severe motion artifacts
- Previously: Use of fiducial markers
  Compensation in:
  - Reconstruction space
  - Projection space

Image-based compensation possible?

Context



- Weight-bearing acquisitions:
  - → From standing upright through to deep squats (65° flexion)
- Involuntary knee motion during scans
  - → Severe motion artifacts
- Previously: Use of fiducial markers
Compensation in:
  - Reconstruction space
  - Projection space

Image-based compensation possible?

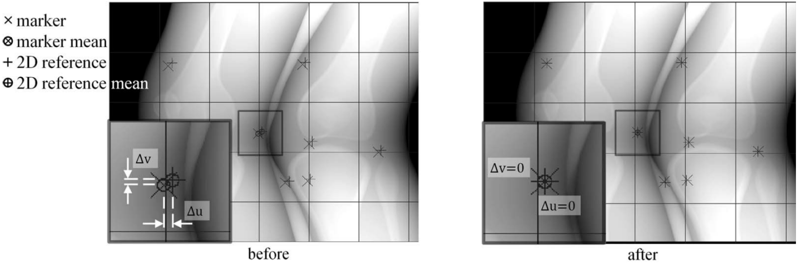
Outline

- **Review of the marker-based approach**
- **Introduction to the image-based approach**
- **Results**
- **Conclusions**

Outline: Projection Shifting Algorithm

1. Generate projections of the static 3D scene
    - Estimate static (mean) 3D position of features (e.g. markers)
    - Forward project the scene
2. Calculate projection shifts
3. Apply shifts and back-project

Marker-based Projection Shifting

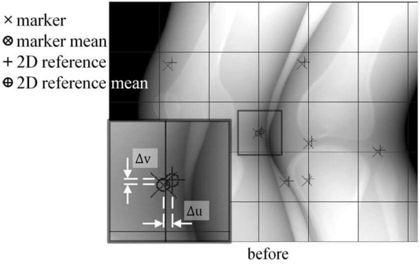


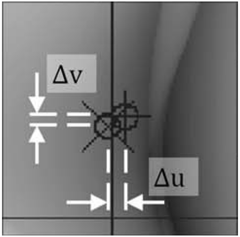
- Detect position $(u, v)_i^{(j)}$ of marker $i = 1, ..., N$ in projection j
- Calculate mean marker position $(\bar{x}, \bar{y}, \bar{z})_i$ in 3D space

Calculate 2D shift:

$$(\Delta u, \Delta v)^{(j)T} = \frac{1}{N} \sum_i \left(\mathbf{P}^{(j)} \cdot \bar{\mathbf{x}}_i^T - (u, v)_i^{(j)T} \right)$$

Marker-based Projection Shifting





- Detect position $(u, v)_i^{(j)}$ of marker $i = 1, \ldots, N$ in projection j
- Calculate mean marker position $(\bar{x}, \bar{y}, \bar{z})_i$ in 3D space

Calculate 2D shift:

$$(\Delta u, \Delta v)^{(j)T} = \frac{1}{N} \sum_i \left(\mathbf{P}^{(j)} \cdot \bar{\mathbf{x}}_i^T - (u, v)_i^{(j)T} \right)$$

Image-based Projection Shifting

Use image registration to calculate 2D projection shifts.

- Estimate of motion-corrected projections
  1. FDK-type uncompensated reconstruction
  2. Gaussian smoothing
  3. Maximum-Intensity-Projections (MIPs) of the volume
     $\rightarrow$ MIPs dominated by high-intensity structures
- Calculate projection shifts $(\Delta u, \Delta v)^{(j)}$
  1. Registration of MIPs to motion-corrupted projections
     $\rightarrow$ Mutual information in 4 scale-space levels
- Shift and reconstruct

Image-based Projection Shifting

Use image registration to calculate 2D projection shifts.

- Estimate of motion-corrected projections
  1. FDK-type uncompensated reconstruction
  2. Gaussian smoothing
  3. Maximum-Intensity-Projections (MIPs) of the volume
     $\rightarrow$ MIPs dominated by high-intensity structures

- Calculate projection shifts $(\Delta u, \Delta v)^{(j)}$
  1. Registration of MIPs to motion-corrupted projections
     $\rightarrow$ Mutual information in 4 scale-space levels

- Shift and reconstruct

Image-based Projection Shifting

Use image registration to calculate 2D projection shifts.

- Estimate of motion-corrected projections
  1. FDK-type uncompensated reconstruction
  2. Gaussian smoothing
  3. Maximum-Intensity-Projections (MIPs) of the volume
     $\rightarrow$ MIPs dominated by high-intensity structures
- Calculate projection shifts $(\Delta u, \Delta v)^{(j)}$
  1. Registration of MIPs to motion-corrupted projections
     $\rightarrow$ Mutual information in 4 scale-space levels
- Shift and reconstruct

Image-based Projection Shifting

Use image registration to calculate 2D projection shifts.

- Estimate of motion-corrected projections
  1. FDK-type uncompensated reconstruction
  2. Gaussian smoothing
  3. Maximum-Intensity-Projections (MIPs) of the volume
     $\rightarrow$ MIPs dominated by high-intensity structures
- Calculate projection shifts $(\Delta u, \Delta v)^{(j)}$
  1. Registration of MIPs to motion-corrupted projections
     $\rightarrow$ Mutual information in 4 scale-space levels
- Shift and reconstruct

Remarks on Mutual Information

How much information about **m** is contained in **f**

Mutual information

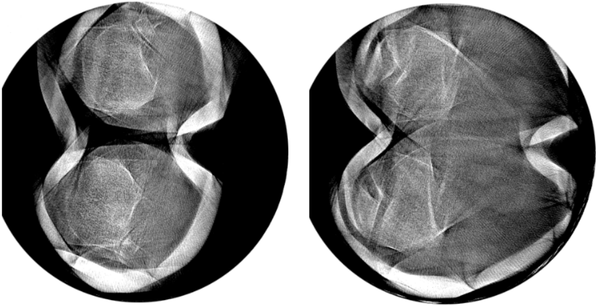
$$MI\,(m(\mathbf{x}), f\,(T(\mathbf{x}))) = H\,(m(\mathbf{x})) + H(f\,(T(\mathbf{x}))) - H\,(m(\mathbf{x}), f\,(T(\mathbf{x})))$$

- Marginal and joint entropy: $H(y)$, $H(y, z)$
- Calculated from histograms: Parzen Window approximation

$\rightarrow$ No explicit form of dependency needed.

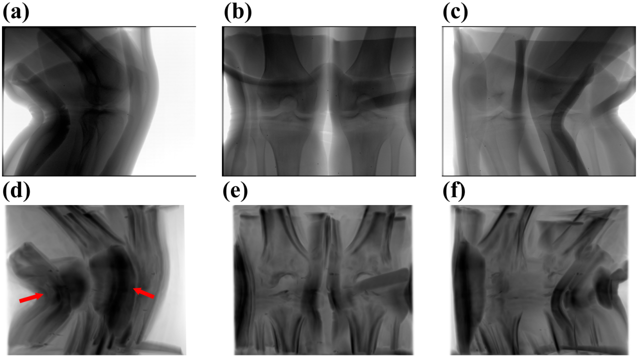
But the histograms must be "related".

Procedure



- Perform FDK-type reconstruction
  $\rightarrow$ Modeling clay to avoid detector saturation

Procedure



- Calculate MIPs and register to acquisitions
  $\rightarrow$ Note clay artifact in MIPs

Experiments:

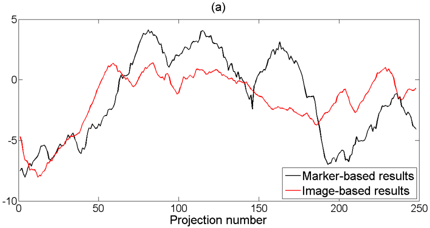
- Five healthy volunteers imaged
- Standing upright, 35° and 65° flexion

→ Two scans with significant motion artifact shown
Scan A at 35° and Scan B at 65° flexion

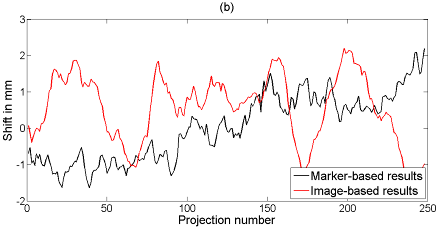
Evaluation:

- Qualitatively: visual inspection
- Quantitatively: marker-based results (gold standard)

Results: Scan A



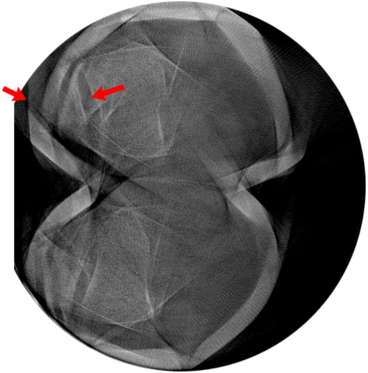
Detector u-coordinate



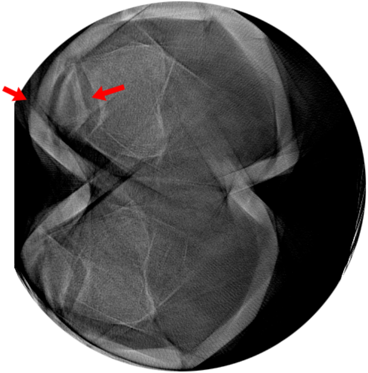
Detector v-coordinate

Error: $2.89\,mm \pm 1.24\,mm$ (uncorrected: $3.50\,mm \pm 1.90\,mm$)

Results: Scan A

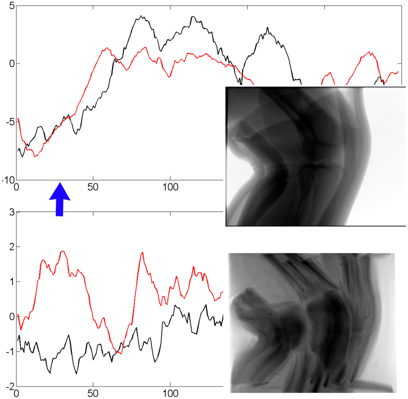


Uncompensated reconstruction



Proposed method

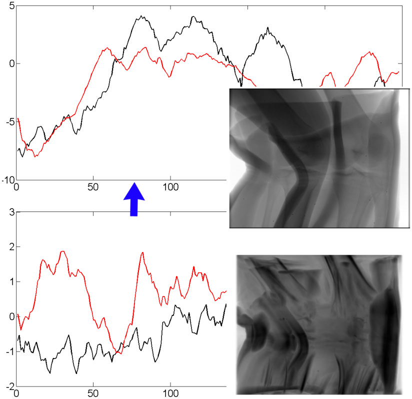
Remarks



- Both knees "aligned"
- Boundaries in *u*-direction pronounced
- Boundaries in *v*-direction suppressed (artifact)

- Structures resulting from overlap not present in MIPs
- Registration becomes more challenging

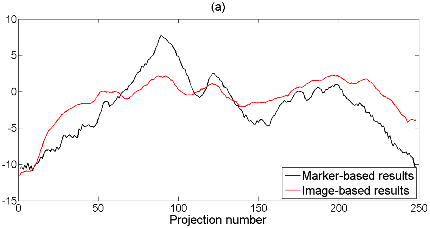
Remarks



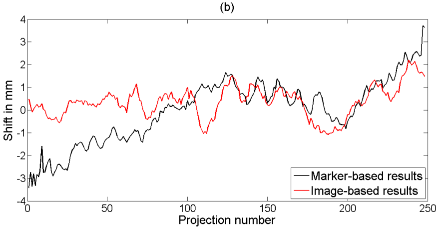
- Both knees "aligned"
- Boundaries in *u*-direction pronounced
- Boundaries in *v*-direction suppressed (artifact)

- Structures resulting from overlap not present in MIPs
- Registration becomes more challenging

Results: Scan B



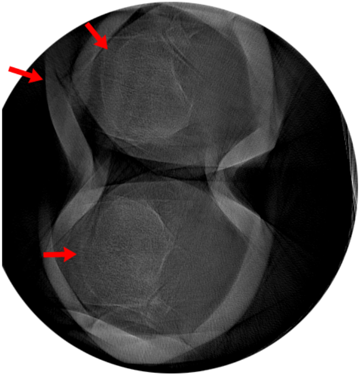
Detector u-coordinate



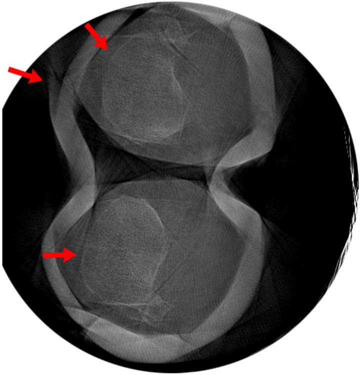
Detector v-coordinate

Error: $2.90\ mm \pm 1.43\ mm$ (uncorrected: $4.10\ mm \pm 3.03\ mm$)

Results: Scan B



Uncompensated reconstruction



Proposed method

Observations

Mean error after correction remains significant in both scans.

Can we get better with iterative application of the method?

Iterative application did not help with the current pipeline.

Possible reasons:

- Using MIPs as reference projections is not optimal
- Mutual information cannot handle the given problem

Performance w.r.t. Marker-based Method

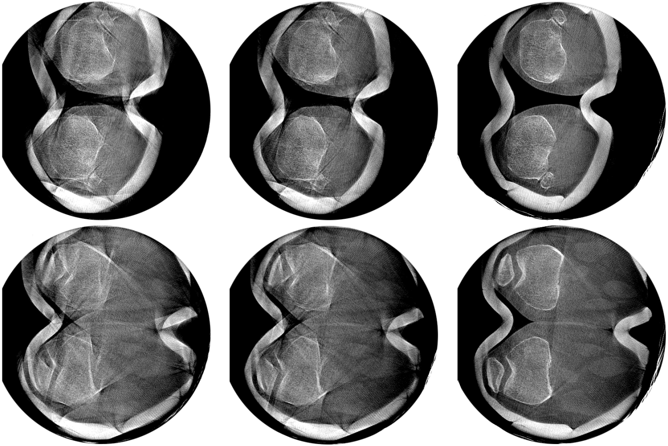


Figure: Uncompensated, proposed and marked-based reconstructions

Discussion and Conclusion

Motion must be visible in high-intensity structures

→ Biased registration in the presence of artifacts (modeling clay)

Stable registration remains challenging

- MIPs & acquisition: dissimilar intensity range and appearance

→ Best similarity metric?

→ Use iterative reconstruction and integrated projections?

3D motion compensation using 3D/2D registration

First step towards automatic image-based motion compensation for weight-bearing knee imaging

Discussion and Conclusion

Motion must be visible in high-intensity structures

→ Biased registration in the presence of artifacts (modeling clay)

Stable registration remains challenging

- MIPs & acquisition: dissimilar intensity range and appearance

→ Best similarity metric?

→ Use iterative reconstruction and integrated projections?

3D motion compensation using 3D/2D registration

First step towards automatic image-based motion compensation for weight-bearing knee imaging