Fluoroscopic Navigation for Robot-Assisted Orthopedic Surgery

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C-arm Fluoroscopy for Orthopedic Surgery

C-arm is a commonly used machine in most orthopedic operating rooms

- X-ray imaging is fast, low-cost, supplies in-depth structures of the patient anatomy
- Consecutive fluoroscopic shots present intraoperative structure changes

Goal: Guide the surgeon to operate the surgical tool and evaluate the performance

[1] Image from: https://www.philips.com/a-w/about/news
Fluoroscopic Guidance Challenges

3D information is collapsed in X-ray projective imaging

- The clinicians estimate the critical 3D information through “mentally mapping”
  - Intraoperative tool-to-tissue relationship
  - Relationship with respect to pre-operative planning

Failed estimations can lead to large operation errors

Robot-Assisted Orthopedic Surgery

Robotic Surgical System

- Better precision, more stable, safer than human’s freehand
- Automates the control of more complicated surgical tools

Navigation system is critical

- Quantitatively computes 3D tool to tissue relationship
- Navigates the robotic surgical tool to planning positions
Concept of Fluoroscopic Navigation System

- Pre-operative Planning
- Assessment
- Intra-operative Registration
- Surgical Tool Positioning

Planning trajectory
Concept of Fluoroscopic Navigation System

- Pre-operative Planning
- Intra-operative Registration
- Surgical Tool Positioning
- Assessment

Image-based 2D/3D Registration

Planning trajectory
Post-op Estimation

Robot End Effector (ee)
Robot Base
Intra-operative Registration Fundamentals

2D/3D Registration

Given the following:
• 2D target image \( I \)
• 3D volume \( V \)
• pose parameter \( \theta \in SE(3) \)
• a Digitally Reconstructed Radiography (DRR) operator \( P \)
• a similarity function \( S \)

2D/3D Registration solves the following optimization:

\[
\theta = \min_{\theta} S(I, P(V; \theta))
\]

When generalizing to multiple \( m \) objects and \( n \) images, including pose regularization term \( R \):

\[
\{\theta_m\} = \min_{\theta_m} \sum_{n=0}^{N} S(I_n, P(V_n; \theta_m)) + R(\theta_m)
\]

\( m \in \{0, \ldots, M\}, n \in \{0, \ldots, N\} \)

Challenges

2D/3D Registration Challenges

Narrow Capture Range

• Local minima of conventional hand-crafted similarity function, such as Gradient Normalized Cross Correlation (Grad-NCC)
• Requires the initialization close to the ground truth

Ambiguity

• Single-view registration is ambiguous along depth direction due to collapsed information in projective geometry
• More serious if the search space is more complex, such as deformable registration
Challenges

Bone Anatomy Registration Challenges:

Proximal Femur

- Lack of distinct features in X-ray image
- Ambiguous in axial rotation

Spine Vertebrae

- Multi-component, size is smaller
- Shape deforms intra-operatively

Surgical Tool Registration Challenges:

Rigid Bone Drilling & Injection Device

- Metallic guide is symmetric, no texture under X-ray
- Orientation accuracy is critical

Dexterous Continuum Manipulator

- Small and flexible
- Shape estimation is critical

[4] X-ray image resources:
https://radiopaedia.org/cases/normal-lumbar-spine


Clinical Background

Femoroplasty

- A preventive therapeutic procedure proposed for patients with osteoporosis
- Inject bone cement to an osteoporotic femur to reduce the risk of fracture

Previous Efforts: Hand-held Injection

Fiducial-based Navigation


Previous Efforts: Hand-held Injection

Fiducial-based Navigation

Limitations:

• Bone pin fiducial introduces additional incision to the patient
• Hand-held drilling is not stable
• X-ray field-of-view is limited to capture all fiducials


Robot-Assisted Femoroplasty

Proposed Objectives

Robotic Drilling/Injection

• UR-10 as a steady positioning robot arm

Fiducial-free Navigation

• Use purely C-arm X-ray images to estimate the critical $T_{\text{Femur}}$
Navigation Pipeline for Robot-Assisted Femoroplasty

**Inputs**
- Patient CT
- Femur Segmentation
- Drilling/Injection Device Model

**Robot Navigated to Planning Trajectory**

**Estimate Femur and Robot Pose with Intensity-Based 2D/3D Registration**

**Preoperative CT scan** → **Femur segmentation** → **Finite element model** → **Planning paradigm** → **Optimal Injection path**

1. FE Optimization
2. Matching Spheroids
3. Hydrodynamic simulation

**Navigation Pipeline for Robot-Assisted Femoroplasty**

**Patient-Specific CT Scans and Bone Segmentation**

**Inputs**
- Patient CT
- Femur Segmentation
- Drilling/Injection Device Model

**Custom-Designed Bone Drilling & Injection Device**

Credit: Designed by Mahsan Bakhtiarinejad and Dr. Amir Farvardin

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Overall Femoroplasty Navigation Pipeline

Inputs
- Patient CT
- Femur Segmentation
- Drilling/Injection Device Model

Preoperative Planning

Intra-operative Registration

Assessment

Surgical Tool Positioning

Drilling/Injection Trajectory

Target Point

Entry Point

Credit: Biomechanical Planning Module developed by Dr. Amir Farvardin and Mahsan Bakhtiarinejad

Registration Methods

Femur Registration Pipeline

Multi-view Data Acquisition

Registration Methods

Pelvis Registration

Stage 1:

- Automatic Pelvis Initialization
- Single-view Pelvis 2D/3D Registration
- Multi-view Pelvis 2D/3D Registration

Multiple view Fluoroscopies

Reason:

- Pelvis registration is more accurate than femur\[^{11}\], because it is bigger and has more textures
- Pelvis registration estimates multi-view C-arm geometry
- Initialize and regularize femur registration


Automatic Initialization

Solve a PnP problem using corresponding landmarks

Concurrent Segmentation and Localization?

Registration Methods

Femur Registration


Injection Device Registration

Fiducial-free 2D/3D registration for robot-assisted femoroplasty. IEEE transactions on medical robotics and bionics, 2(3), pp. 437-446.
Registration Simulation Study

Simulated 1,000 Registrations with Randomized Geometries

Table: Simulation Error

<table>
<thead>
<tr>
<th></th>
<th>mean</th>
<th>median</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entry Point (mm)</td>
<td>1.70 ± 0.94</td>
<td>1.64</td>
</tr>
<tr>
<td>Guide Tip (mm)</td>
<td>0.93 ± 0.81</td>
<td>0.74</td>
</tr>
<tr>
<td>Relative (mm)</td>
<td>1.26 ± 0.74</td>
<td>1.15</td>
</tr>
<tr>
<td>Femur Path (%)</td>
<td>0.63 ± 0.21</td>
<td>0.62</td>
</tr>
<tr>
<td>Guide Path (%)</td>
<td>0.17 ± 0.19</td>
<td>0.14</td>
</tr>
</tbody>
</table>

Femur entry point relative to Guide tip

\[ D_{ij} = \frac{\| p_{\text{arm}} - p_{\text{guide}} \|}{\| p_{\text{arm}} \|} \]

Joint Histogram of Translation and Rotation Errors


Femoroplasty Registration Cadaver Experiment

Cadaveric Experiment Setup

Ground truth pose obtained using metallic BB annotations, solving a PnP problem.

Femoroplasty Registration Cadaver Experiment

Cadaveric Experiment Result

Table: Positional Registration Error of Six Individual Trials

<table>
<thead>
<tr>
<th>mm</th>
<th>Trial1</th>
<th>Trial2</th>
<th>Trial3</th>
<th>Trial4</th>
<th>Trial5</th>
<th>Trial6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entry Point</td>
<td>1.34</td>
<td>2.44</td>
<td>2.41</td>
<td>1.99</td>
<td>3.67</td>
<td>4.38</td>
</tr>
<tr>
<td>Device Tip</td>
<td>3.17</td>
<td>0.84</td>
<td>1.48</td>
<td>2.93</td>
<td>1.79</td>
<td>0.83</td>
</tr>
<tr>
<td>Relative</td>
<td>1.98</td>
<td>2.88</td>
<td>3.44</td>
<td>1.32</td>
<td>1.94</td>
<td>4.28</td>
</tr>
</tbody>
</table>

Femur entry point relative to Guide tip

\[
\text{Dist}_{\text{rel}} = \left( p_{\text{entry}}^{\text{target}} - p_{\text{entry}}^{\text{arm}} \right) - \left( p_{\text{arm}}^{\text{target}} - p_{\text{arm}}^{\text{arm}} \right) \parallel \text{Guide Tip} \\
\text{Mean Relative Error: } 2.64 \pm 1.10 \text{ mm}
\]

Clinically Acceptable Error: 2 - 3 mm


Overall Femoroplasty Navigation Pipeline

Inputs
- Patient CT
- Femur Segmentation
- Drilling/Injection Device Model

Preoperative CT scan

Femur segmentation

Finite element model

Planning paradigm

- 1. FE Optimization
- 2. Matching Spheroids
- 3. Hydrodynamic simulation

Robot Navigated to Planning Trajectory

Estimate Femur and Robot Pose with Intensity-Based 2D/3D Registration

Pre-operative Planning

Assessment

Intra-operative Registration

Surgical Tool Positioning
System Calibration

Hand-eye Calibration

- Solve an axxb problem

\[(\mathbf{T}_\text{c}_\text{arm})_i \cdot \mathbf{T}^\text{DF}_\text{DI}_i \cdot (\mathbf{T}^\text{SF}_\text{DF})_i = (\mathbf{T}_\text{c}_\text{arm})_i \cdot \mathbf{T}^\text{DF}_\text{DI}_i \cdot (\mathbf{T}^\text{SF}_\text{DF})_i\]

\[\mathbf{T}_\text{c}_\text{arm}^{-1} \cdot \mathbf{T}^\text{DF}_\text{DI}_i \cdot \mathbf{T}^\text{SF}_\text{DF} = (\mathbf{T}^\text{SF}_\text{DF})_i^{-1} \cdot \mathbf{T}^\text{DF}_\text{DI}_i \cdot \mathbf{T}_\text{c}_\text{arm}\]

\[AX = XB\]

Note:
The tracker is used for closed-loop control, because the UR forward kinematic accuracy is insufficient for this task.

Credit: Closed-loop control module developed by Henry Phalen

Note:
The tracker is used for closed-loop control, because the UR forward kinematic accuracy is insufficient for this task.

Credit: Closed-loop control module developed by Henry Phalen

Cadaveric Drilling and Results

Post-op CT Analysis

Drilling after the guide is positioned

X-ray before Drilling
X-ray after Drilling

Target point error: 2.64 mm
Insertion point error: 3.28 mm
Orientation error: 2.30 degrees

Clinical Evaluation

Yield load estimation with biomechanical simulation:

- 33% increase of yield load with the measured trajectory error
- Previous biomechanical studies show positive augmentation effects when distance error ~ 8mm, rotation error ~ 5° [13]

Credit: Yield load estimation performed by Mahsan Bakhtiarinejad
Conclusion and Contributions

• An automatic, intensity-based 2D/3D registration method for pose estimation of the femur

• A fiducial-free navigation pipeline for robot-assisted femoroplasty

• Evaluated the navigation methods with simulation and cadaver experiments. The results meet clinical requirements, and suggest feasibility to be used for related orthopedic applications

Acknowledgment

Dr. Robert Grupp: Developed 2D/3D registration software infrastructure - xreg, contributed to femur registration algorithm design

Mrs. Mahsan Bakhtiarinejad and Dr. Amir Farvardin: Designed the injection unit, developed biomechanical analysis pipeline, contributed to cadaver experiments and analysis

Mr. Henry Phalen: Developed the robot closed-loop control module

Dr. Liuhong Ma and Ms. Mareike Thies: Helped with cadaver experiments

Related Publications/Manuscripts:


Clinical Background

Pain Relief from Spine Epidural Injections

- Globally, between 60-80% of people are expected to experience lower back pain in lifetime
- 30 million epidural injections worldwide
- Effectiveness is highly variable (50-70% efficacy rates)
- Failed injections can result in catastrophic spinal cord of nerve root injuries, even paralysis

Clinical Background

Clinical Practice and Challenges

The clinician acquires several fluoroscopic images before and during the manual insertion of the needle.

Lack of 3D needle position estimation with respect to the spine vertebrae.

Clinical’s needle injection under fluoroscopic guidance.[15]

Autonomous Robotic Spinal Needle Insertion

Proposed Objectives

Robotic Needle Injection

- Robotic End Effector delivers the needle.

Fiducial-Free Navigation

- Use purely C-arm X-ray images to estimate the critical $T^\text{Spine}_{DI}$.
Spine Injection Navigation Pipeline

Overall Spine Injection Navigation Pipeline


* indicates joint first co-authors

Credit: Interactive Planning Module developed by Henry Phalen
Spine Injection Navigation Pipeline

Pre-operative Planning

Registration & Navigation

Assessment

Intra-operative Registration

Surgical Tool Positioning

Inputs:
- Planning
- Pre-operative Planning
- Intra-operative Registration
- Assessment
- Surgical Tool Positioning


* indicates joint first co-authors

Registration Methods

Injection Device Registration Pipeline

Stage 1:
- Multiple view Fluoroscopies

Stage 2:
- Single-view Joint Injection Device Registration
- Multi-view Injection Device Registration


* indicates joint first co-authors
Registration Methods

Joint Injection Device Registration

Stage 1:

Multiple - view Injection Device Registration

C-arm is fixed, robot moves to multiple configurations


* indicates joint first co-authors
Simulation Study of Injection Device Registration

Simulated 1,000 Registrations with Randomized Geometries

Table: Injection Device Registration Pose Errors

<table>
<thead>
<tr>
<th></th>
<th>Translation (mm)</th>
<th>Rotation (degree)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single Object</td>
<td>2.15 ± 1.57</td>
<td>1.62 ± 1.40</td>
</tr>
<tr>
<td>Joint Registration</td>
<td>1.73 ± 1.17</td>
<td>0.91 ± 0.92</td>
</tr>
</tbody>
</table>

Registration Pipeline

Stage 1:
- Multiple view Fluoroscopies
- Single-view Joint Injection Device Registration
- Multi-view Injection Device 2D/3D Registration

Stage 2:
- Single-view Spine 2D/3D Registration
- Multi-view Vertebrae-by-Vertebrae Registration


* indicates joint first co-authors
Registration Pipeline

- Single-view rigid spine registration provides a coarse estimation
- Precise pose estimation of individual vertebra is achieved by multi-component optimization

\[
\min_{s, \theta} \sum_{k=1}^{K} S(I_k, P, \sum_{n=1}^{V} V_n, T_{Corra}, T_{Corra})
\]

Loop every vertebra

Stage 2:
- Single-view Spine 2D/3D Registration
- Multi-view Vertebrae-by-Vertebrae Registration

Spine Registration Simulation Study

Simulate Spine Deformation using CT Segmentations

3D Rendering of Simulated Spine Deformations
Rotation sampled uniformly from [-12.5, 12.5] degrees

Synthetic X-ray of Spine Segmentation and CT

Spine Range of Motion\[16\]

40 - 60 degrees for normal adult


Spine Registration Simulation Study

Single-view C-arm Geometry

Rigid Spine Registration

Vertebrae-by-Vertebrae Registration


* indicates joint first co-authors

Spine Registration Simulation Study

Multi-view C-arm Geometry

Rigid Spine Registration

Vertebrae-by-Vertebrae Registration


* indicates joint first co-authors
Spine Registration Simulation Study

Table: Numeric Registration Pose Error

<table>
<thead>
<tr>
<th></th>
<th>Translation (mm)</th>
<th>Rotation (degrees)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single-view</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rigid Spine</td>
<td>4.79±2.36</td>
<td>2.79±1.70</td>
</tr>
<tr>
<td>Vertb-by-Verb</td>
<td>3.50±2.91</td>
<td>1.05±1.88</td>
</tr>
<tr>
<td>Multi-view</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rigid Spine</td>
<td>3.69±1.60</td>
<td>2.89±1.23</td>
</tr>
<tr>
<td>Vertb-by-Verb</td>
<td>0.76±0.28</td>
<td>0.88±0.68</td>
</tr>
</tbody>
</table>

Overall Spine Injection Navigation Pipeline
System Setup

**Hand-eye Calibration**

- Introduced before

**Needle Tip Calibration**

- Triangulate the needle tip point in the injection model frame using 6-7 X-ray images

Credit: The Syringe mount is designed by Justin Ma

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Robotic Spine Needle Injection Cadaver Study

**Performed 10 Robotic Needle Injections**


* indicates joint first co-authors
Robotic Spine Needle Injection Cadaver Study

Performed 10 Robotic Needle Injections

X-ray Image after Insertion  Picture of the Inserted Needles

Robot Injection Experiment Video

Pre-operative Planning  Intra-operative Registration
  Assessment  Surgical Tool Positioning

Experienced Clinician Manual Injection

Performed 10 Needle Injections using the same Plannings

Dr. Akhil Chhatre  Dr. David Cohen

X-ray  Post-op CT  X-ray  Post-op CT

Post-op CT  X-ray
Spine Injection Results

Table: Cadaveric Needle Injection Accuracy

<table>
<thead>
<tr>
<th>ID</th>
<th>Needle Tip Error (mm)</th>
<th>Orientation Error (degrees)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Robot</td>
<td>Surgeon</td>
</tr>
<tr>
<td>1</td>
<td>3.13</td>
<td>9.46</td>
</tr>
<tr>
<td>2</td>
<td>6.13</td>
<td>11.35</td>
</tr>
<tr>
<td>3</td>
<td>7.02</td>
<td>6.17</td>
</tr>
<tr>
<td>4</td>
<td>7.46</td>
<td>12.29</td>
</tr>
<tr>
<td>5</td>
<td>4.36</td>
<td>6.88</td>
</tr>
<tr>
<td>6</td>
<td>1.54</td>
<td>8.46</td>
</tr>
<tr>
<td>7</td>
<td>5.14</td>
<td>3.36</td>
</tr>
<tr>
<td>8</td>
<td>8.01</td>
<td>7.02</td>
</tr>
<tr>
<td>9</td>
<td>1.57</td>
<td>5.28</td>
</tr>
<tr>
<td>10</td>
<td>6.85</td>
<td>5.56</td>
</tr>
</tbody>
</table>

Mean: 5.00 ± 2.36 7.58 ± 2.80 3.61 ± 1.93 9.90 ± 4.73

Post-op Analysis

- Took post-op CT scans with inserted needles
- 3D/3D Registration between pre-op and post-op CT of each individual vertebra
- Annotated target/entry points for comparison

Clinical Evaluation

Triangle Safety Zone

- Injections through the safety triangle allow the steroid to be injected more effectively and safely
- All of our injections were within the triangle safety zones

Conclusion and Contributions

• An autonomous fluoroscopy-guided robotic spine needle injection system

• Present the superiority of multi-view, multi-component 2D/3D registration over single-view, single object 2D/3D registration with simulation experiments

• Present the improved performance using our robotic injections compared to clinician’s manual injections in controlled cadaver experiments

Acknowledgment

Mr. Henry Phalen: Developed the interactive needle planning module, the robot closed-loop control module, contributed to system calibration and trouble shooting, jointly worked on both phantom and cadaver experiments, and post-op analysis

Mr. Adam Margalit: Built the spine testing phantom (not presented here), provided clinical guidance, coordination and equipment support, jointly worked on both phantom and cadaver experiments

Mr. Justin Ma: Developed the robot closed-loop control module

Mr. Ping-Cheng Ku: Helped annotate the triangle safety zone for post-op analysis

Dr. Akhil Chhatre and Dr. David Cohen: Performed manual needle injections

Related Publications/Manuscripts:


* indicates joint first co-authors
Core Decompression of the Hip

Osteonecrosis

- A disease that results from loss of blood supply to the bone
- Usually progresses to femoral head collapse, and eventually total hip arthroplasty
- Core Decompression -- Reduce the pressure in the femoral head with osteonecrosis

Less-invasive Surgical Procedure

- Access the lesion through the narrow femoral neck by drilling
- Remove and grafting the lesion

Continuum Manipulator

Custom-designed Continuum Manipulator with embedded Shape Sensing

- Accurate intraoperative pose and shape feedback during bone drilling is challenging

FBG Sensor

\[ \downarrow \]

Curvature

\[ \downarrow \]

Model

\[ \downarrow \]

Position of Tip wrt Base

Challenges of FBG Shape Sensing

- Fiber Bragg Grating (FBG) sensing doesn’t have enough sensing points, which might not be accurate

- Large errors when touching obstacles

- Internal sensing does not close the registration loop with respect to the bone
Previous Efforts

Limitations of Otake et al.’s work

- Manual initialization
- Only tested in simulation. The simulation was not yet realistic
- Not integrated/tested with the robot system


Motivation

X-ray Image-based navigation of the CM

- **Rigid** Pose estimation of femur and the CM
- **Flexible** CM Shape estimation
- Robot relative to the bone anatomy, $T_{Femur}^{CM}$

CM Model and X-ray Simulation

![CM 3D Model and Example X-ray Simulation](image)

**CM Navigation Pipeline**

1. **Pre-operative Calibration**
2. **Detection and Initialization**
3. **Registration and Navigation**

Learning-based CM Detection

Concurrent segmentation and landmark detection[21]

Table: CM Detection Accuracy

<table>
<thead>
<tr>
<th></th>
<th>Landmark Error (mm)</th>
<th>Segmentation DICE Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simulation</td>
<td>0.449 ± 0.525</td>
<td>0.993 ± 0.002</td>
</tr>
<tr>
<td>Real X-ray</td>
<td>2.62 ± 1.05</td>
<td>0.920 ± 0.068</td>
</tr>
</tbody>
</table>


Single-view CM Registration

- Automatic initialization of CM registration
- The landmarks regularize the registration search space (reprojection penalty)

CM Registration

Severe Registration Ambiguity

• Single-view registration by itself has ambiguity

• The CM is small, symmetric and flexible

Affects the hand-eye calibration accuracy

• Solve an axby problem

Joint CM Registration

Our Solution to Balance Registration Ambiguity

• Use robot kinematics to jointly register multiple CM configurations together

• A modified, image-based hand-eye calibration method

\[
\min_{T_{CM}^a, T_{CM}^b \in SE(3)} \sum_{m=1}^{M} S(I_m, P(\sum_{j=1}^{J} V_j T_{CM}^a T_{CM}^b T_{ee, ref}))
\]
CM Registration Simulation Study

Single-view Registration

Multi-view Registration

Joint CM Registration

CM Registration Simulation Study

Multi-view Registration

CM Registration Simulation Study

Joint CM Registration
Simulation Study Results

Histogram of Single-view Registration Error

Histogram of Multi-view Registration Error

Histogram of Joint CM Registration Error

Histogram of Single-view Registration CM Base Error

Histogram of Multi-view Registration CM Base Error

Histogram of Joint CM Registration CM Base Error

System Calibration

CM Hand-eye Calibration

Mean Tip Difference: 2.15 ± 0.50 mm

Core Decompression Cadaveric Experiment

Ground truth poses were obtained by solving a PnP problem using BB and fiducial landmarks.

CM Cadaveric Experiment

Table: CM Tip & Femur Entry Point Error

<table>
<thead>
<tr>
<th>Trial ID</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
<th>V</th>
</tr>
</thead>
<tbody>
<tr>
<td>CM Tip Position (mm)</td>
<td>2.73</td>
<td>2.44</td>
<td>2.77</td>
<td>4.20</td>
<td>2.09</td>
</tr>
<tr>
<td>Femur Entry Point (mm)</td>
<td>1.21</td>
<td>2.23</td>
<td>1.91</td>
<td>2.35</td>
<td>2.04</td>
</tr>
<tr>
<td>Relative (mm)</td>
<td>2.95</td>
<td>3.31</td>
<td>3.65</td>
<td>4.10</td>
<td>1.83</td>
</tr>
</tbody>
</table>

Femur entry point relative to CM tip
Mean Error: 2.86 ± 0.80 mm


Conclusion and Contributions

Automatic Registration Pipeline
- A learning-based continuum manipulator detection method in X-ray images

Balanced Registration Ambiguity
- Jointly register multiple CM together and a modified hand-eye calibration method

System Validation
- Verified the feasibility of applying purely fluoroscopic image-based registration for the CM navigation in simulation and cadaver experiments
Acknowledgment

Mr. Henry Phalen: Contributed to registration algorithm design, helped with the continuum manipulator calibration and cadaver experiments

Dr. Shahriar Sefati: Developed the continuum manipulator optical marker-based hand-eye calibration and control modules, helped with the system testing and algorithm design

Mr. Justin Ma: Developed the improved version of continuum manipulator

Related Publications/Manuscripts:


* indicates joint first co-authors
Recap

Machine Learning X-ray Detection Tasks
• Automatic Registration Initialization

How do we generate training data?
Motivation

SyntheX: Realistic Synthesis for X-ray Image Analysis

Unique Cadaveric Pelvic X-ray Dataset

A cadaveric hip dataset\[22\]
- 6 cadaveric specimens
- 366 X-ray images
- All have registered “ground truth” pose of corresponding CT scans

14 anatomical landmarks & 6 pelvic segmentations

Credit: Dr. Robert Grupp published this valuable dataset


Precisely Matched Simulation-Real Database
Precisely Controlled Sim2Real Benchmark Experiments

Sim2Real Techniques
- Domain Randomization
- Domain Adaptation
  - CycleGAN
  - Adversarial Discriminative Domain Adaptation

Concurrent Segmentation and Landmark Detection

**Hip Imaging Downstream Task**

Ablation Simulators

- Real X-ray
- Realistic
- Heuristic
- Naive

DeepDRR\(^{[23]}\)
- 3D Organ Segmentation
- Specified Attenuation
- Photon Spectrum
- Noise Sampling and Scattering

Xreg DRR\(^{[24]}\)
- Simple Thresholding
- Noise Sampling

Naive DRR
- Only line integration


Domain Randomization

- Regular DR: Gaussian noise; Contrast; Random Crop
- Strong DR:

(a) No DR. (b) Inverting. (c) Pepper and salt noise injection. (d) Contrast. (e) Affine transform. (f) Blurring. (g) Dropout. (h) Sharpening and embossing. (i) Pooling. (j) Element-wise multiplication. (k) Box corruption. (l) Elastic effect.
Landmark Detection Result – Domain Randomization

- **Activated threshold**
- **Heatmap response**

![Graphs showing comparison between different techniques](image)

Ideal Curve

Scaled-up Simulation

- Annotated 20 CT scans from the New Mexico Decedent Image Database[24]
- Simulate 10k X-rays
- More sampled geometries

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[24] Edgar, HJH; Daneshvari Berry, S; Moses, E; Adolphs, NL; Bridges, P; Nolte, KB (2020). New Mexico Decedent Image Database. Office of the Medical Investigator, University of New Mexico. doi.org/10.25827/5s8c-n515.
Landmark Detection Result – Scaled Up

Scaled-up simulation training outperforms Real2Real!

Qualitative Results of Sim2Real Detection Results
Surgical Tool Detection Downstream Task

Real X-ray → Segmentation → Landmarks

Table: Detection Accuracy

<table>
<thead>
<tr>
<th></th>
<th>Landmark Error (mm)</th>
<th>Dice Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sim2Real</td>
<td>2.13 ± 2.27</td>
<td>0.860 ± 0.115</td>
</tr>
<tr>
<td>Real2Real</td>
<td>1.90 ± 5.49</td>
<td>0.406 ± 0.194</td>
</tr>
</tbody>
</table>

- Real2Real was trained on 200 annotated X-ray images,
- Sim2Real was trained using 20k synthetic images

Conclusion and Contributions

- We quantified the role of domain shift in the deterioration of machine learning model performance from training in simulation to deployment on real data.
- Physics-based Realistic Simulation with DR generalizes the best. Scaling up simulation dataset even outperforms Real2Real.
- SyntheX as a promising alternative for machine learning X-ray imaging tasks.
Acknowledgment

Mr. Benjamin Killeen: Contributed to comparison experiment running

Mr. Yicheng Hu: Contributed to simulation geometry calibration and experiment running

Dr. Robert Grupp: Collected and published the pelvic dataset

Related Publications/Manuscripts:

Recap: 2D/3D Registration Challenge

Narrow Capture Range

- Local minima of conventional hand-crafted similarity function, such as Grad-NCC
- Requires the initialization close to the ground truth

Conventional Intensity-based 2D/3D Registration Strategy:
- CMAES + Patch-based Grad-NCC

Related Work

Pose Regression Methods

Limitations:

- Learning a mapping function from 2D projections is an ill-posed problem, which is prone to strongly overfit to training domain
- Direct pose regression is unconstrained, which can change dramatically if the input image appearance has a tiny difference
Motivation

A More Desired Solution

Traditional DRR Projector is not Differentiable!

- Oversized system matrix $A(\theta)$ to fit in memory
- Conventional optimization strategies are numeric-based methods, such as CMAES


Projective Spatial Transformers (ProST)

ProST -- Differentiable DRR Operator

Spatial Sampling Grid: $G$
- Follows projection geometry

Given a pose parameter $\theta$ and 3D volume $V$ as input, the DRR projection is:

$$I = P(V, \theta)$$

$$= \text{sum} \left( \text{interp} \left( V, T(\theta)G \right) \right)$$

Breakthrough:

$$\frac{\partial P(V, \theta)}{\partial \theta} \quad \text{and} \quad \frac{\partial P(V, \theta)}{\partial V}$$

are differentiable!

Projective Spatial Transformers (ProST)

\[ \theta \in \text{SE}(3) \]

**Example registration using Grad-NCC similarity, optimized by PyTorch built-in SGD optimizer**

ProST 2D/3D Registration Pipeline

**Target Similarity Function -- Geodesic Loss**
- A convex objective function with respect to SE(3) pose parameters

\[ \frac{\partial S_{\text{net}}}{\partial \theta_m} \]

Gradient-driven Double Backward Loss

Geodesic Gradient

CT Segmentation

3D CNN

ProST

\[ I_m \]

Moving Image

\[ I_t \]

Target X-ray Image

CrossViT

\[ S_{\text{Net}} \]

Predicted Similarity

Objective function

How do we learn a better similarity function?

Network Similarity Function Shape

\[ \theta_{\text{gt}} \]

\[ \theta \]

\[ V \]

\[ I_m \]

\[ I_t \]

2D Mov

2D Tar

\[ \theta \rightarrow \text{SE}(3) \]

\[ V \rightarrow \text{3D} \]

\[ I \rightarrow \text{2D} \]

PyTorch C++, CUDA backend
Example Registration using ProST Architecture

ProST Registration using Learned Similarity Function

ProST Registration brings the 3D object much closer to the ground truth pose.

CMAES Start from Initialization (blue)  CMAES Start from ProST (orange)

Experiments and Results

- Our pipeline was trained using 19 CT scans, evaluated on 1,000 synthetic X-rays and 200 real X-rays.

<table>
<thead>
<tr>
<th></th>
<th>Simulation</th>
<th>Real</th>
</tr>
</thead>
<tbody>
<tr>
<td>CMAES from Initialization</td>
<td>32.6</td>
<td>36.0</td>
</tr>
<tr>
<td>CMAES from ProST Registration</td>
<td><strong>82.6</strong></td>
<td>73.2</td>
</tr>
</tbody>
</table>
Experiments and Results

Loss Shape Comparison Network Similarity – Grad-NCC Similarity
For each Degree of Freedom

Network Similarity
Grad-NCC Similarity

Conclusion & Contributions

- A novel ProST module, which enables differentiable volumetric rendering of X-ray images using CT volumes and analytical gradient calculation with respect to pose parameters.

- An innovative end-to-end 2D/3D image registration by learning a convex-shape similarity function.

- Demonstrated that ProST registration largely extends the conventional CMAES registration capture range.
Acknowledgment

Dr. Xingtong Liu: Contributed to ProST design, registration architecture design, and double backward loss.

Ms. Anqi Feng: Contributed to data processing and comparison experiments in extended journal submission

Mr. Wenhao Gu and Mr. Benjamin Killeen: Provided valuable suggestions

Related Publications/Manuscripts:


Summary

**Effective Navigation System**
- Use purely fluoroscopic images
- (Semi-) Automatic registration algorithms
- Robot system-level validation
- Feasibility on variant clinical applications

**Novel AI Frameworks**
- Benefit machine learning X-ray imaging research
- Provide solutions to solve fundamental registration challenges

![Femoroplasty](image1.png)
![SyntheX](image2.png)
![Core Decompression](image3.png)
![Lumbar Epidural Injections](image4.png)
![ProST](image5.png)

Future Work Outlook

**Optimal C-arm view geometry**
- The best view that the registration has the highest chance to succeed

**Patient Motion Verification**
- Automatically detect patient motion and correct registration

**Registration Uncertainty**
- Confidence of the registration pose estimations

Thank you!