



**Literature Review Presentation**

# **Team 07: Real-time Integration of Fully Automatic 2D/3D Pelvic Registration with Robotic X-ray Acquisition**

**Students:**

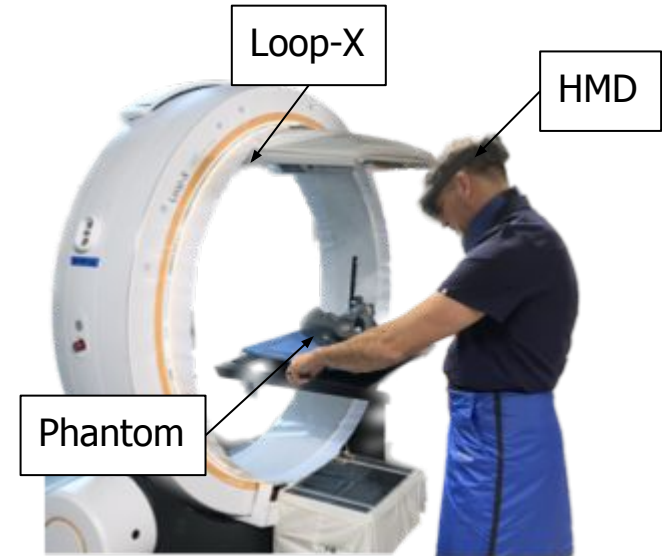
- Jiaming Zhang
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**Mentors:**

- Benjamin Killeen
- Prof. Mathias Unberath

# Project Recap - Background and Project Goal

- Our project aims to develop a pipeline that **automatically perform the 2D/3D registration** process between X-ray images and CT Scan intra-operatively.
  - To be specific, we need to integrate the **image acquisition process, data synthesizing process, landmark detection, and online registration** into one sole software with a user-friendly GUI.
- We also seek to visualize the data with novel projective paradigms on HoloLens.



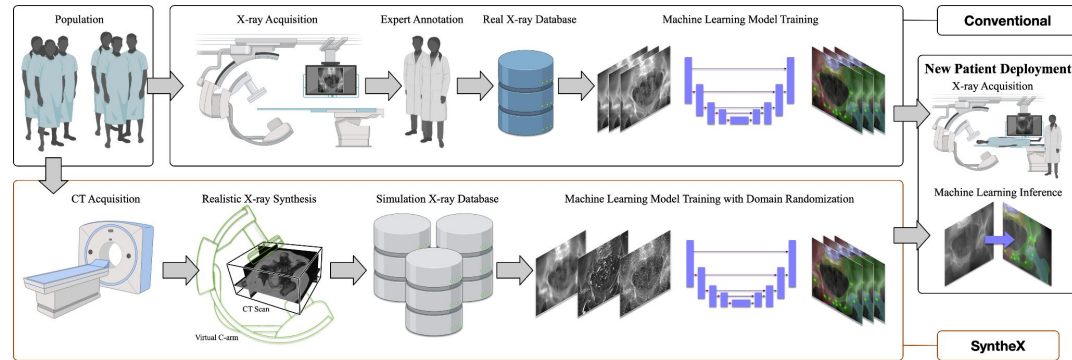
<https://www.brainlab.com/surgery-products/overview-platform-products/robotic-intraoperative-mobile-cbct/>

# Paper Selection

## Paper 1: SyntheX: Scaling Up Learning-based X-ray Image Analysis Through In Silico Experiments

Cong Gao, Benjamin D. Killeen, Yicheng Hu, Robert B. Grupp, Russell H. Taylor, Mehran Armand, Mathias Unberath

In this paper, Dr. Gao proposed an AI-based model transfer paradigm for X-ray image analysis, which furtherly help to perform automatic annotation for intraoperative X-ray image.



[https://github.com/arcadelab/SyntheX/blob/main/fig/synthex\\_overview.png](https://github.com/arcadelab/SyntheX/blob/main/fig/synthex_overview.png)

# Paper Selection

## Paper 1: SyntheX: Scaling Up Learning-based X-ray Image Analysis Through In Silico Experiments

Cong Gao, Benjamin D. Killeen, Yicheng Hu, Robert B. Grupp, Russell H. Taylor, Mehran Armand, Mathias Unberath

### Why do we choose this paper?

- SyntheX is one of the main component of our pipeline. It provides a trained TransUNet Model to perform X-ray annotation.
- This paper also demonstrated that model trained on synthetic data is sufficient to detect the landmarks for the intraoperative X-ray images.

# Background

- Traditionally, to train a model that can perform realistic tasks, like landmark detection for X-ray image, one have to collect **abundant realistic data**, which is a challenging task especially during the operation.
- **Manually annotation** is a process that **involves a considerable amount of time and effort**.
- **Image synthesis** has been shown to be a **potential way to compensate** the deficient dataset [1].
- Chen et al. proposed **TransUNet** [3], which is a powerful neural network for medical image processing. By applying TransUNet, we can easily annotate the X-ray images automatically.

## Summary of the Problem

This paper wants to show that training the deep learning models on synthetic dataset is a viable alternatives for realistic dataset, especially in three scenario, namely, hip-imaging, surgical tool detection and lesion segmentation.

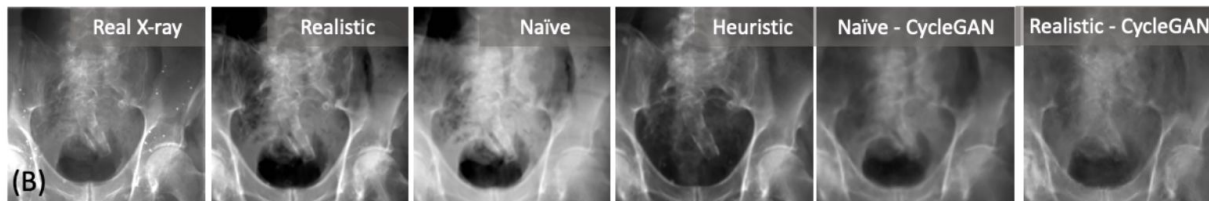
# Experiment Details - Dataset

## Realistic Dataset:

- High-Res CT scans for 6 different cadaveric pelvis.
- 366 corresponding X-ray images

## Synthetic Dataset:

- 20,000 Digitally Reconstructed Radiograph (DRR) generated from 20 CT scans.
- 3 DRR methods are used, namely naiveDRR, xreg DRR and DeepDRR.



Gao, C., "SyntheX: Scaling Up Learning-based X-ray Image Analysis Through In Silico Experiments", *arXiv e-prints*, 2022. doi:10.48550/arXiv.2206.06127.

# Experiment Details - Specification and Evaluation

The proposed method, SyntheX, mitigates the domain gap between DRR dataset and realistic dataset by applying different **domain randomization and domain adaptation** methods.

- **Domain randomization** includes gaussian noise injection, random crop, affine transform, blurring, etc.
- **Domain adaptation** includes CycleGAN and Adversarial Discriminative Domain Adaptation

The model is trained and evaluated in three scenarios:

- **Sim2Sim**: trained and evaluated are both done on synthetic image, mainly to test the functionality
- **Real2Real**: trained on the real image and evaluated on the real image, mainly used as the baseline for the model
- **Sim2Real**: training set is (labeled synthetic x-ray + pure synthetic x-ray) , evaluated on the real x-ray

# Results

- In the given dataset, Sim2Real transfer paradigm gains better performance in L2 error test cases. And its dice score is as good as the model trained in Real2Real case. (Dice Score is an approach to gauge the similarity of two images)
- Also, different domain randomization methods are evaluated and compared to CycleGAN and ADDA. This paper shows that strong randomization is as good as adaptation like cycleGAN.

Table1. Average performance metrics for hip imaging as a mean of 5-fold individual testing on 366 real hip X-ray images.

|                  | Landmark Error (mm) | Dice Score    |
|------------------|---------------------|---------------|
| <i>Sim2Real</i>  | 6.29 ± 6.29         | 0.818 ± 0.221 |
| <i>Real2Real</i> | 8.15 ± 15.30        | 0.759 ± 0.248 |

Table2. Segmentation Dice Score as a mean of 5-fold individual testing on 366 real hip X-ray images. The Dice score ranges from 0 to 1, with larger values corresponding to better segmentation performance.

| Training Data Domain          | 180x180              |                      | 360x360              |                      | 480x480              |                      |
|-------------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
|                               | regular DR           | strong DR            | regular DR           | strong DR            | regular DR           | strong DR            |
| RealXray ( <i>Real2Real</i> ) | 0.775 ± 0.235        | 0.784 ± 0.214        | 0.783 ± 0.232        | 0.759 ± 0.248        | 0.739 ± 0.266        | 0.751 ± 0.265        |
| Realistic                     | 0.730 ± 0.240        | 0.787 ± 0.211        | 0.751 ± 0.241        | 0.760 ± 0.250        | 0.720 ± 0.256        | 0.700 ± 0.279        |
| Heuristic                     | 0.669 ± 0.273        | 0.737 ± 0.249        | 0.683 ± 0.265        | 0.682 ± 0.286        | 0.655 ± 0.277        | 0.668 ± 0.298        |
| Naive                         | 0.689 ± 0.256        | 0.680 ± 0.278        | 0.687 ± 0.266        | 0.572 ± 0.309        | 0.653 ± 0.278        | 0.578 ± 0.305        |
| Realistic-Cyc                 | 0.778 ± 0.217        | 0.778 ± 0.220        | 0.760 ± 0.248        | 0.733 ± 0.267        | 0.741 ± 0.255        | 0.688 ± 0.291        |
| Naive-Cyc                     | 0.784 ± 0.198        | 0.750 ± 0.230        | 0.739 ± 0.254        | 0.736 ± 0.258        | 0.726 ± 0.254        | 0.673 ± 0.292        |
| Realistic-ADDA                | 0.767 ± 0.224        | 0.754 ± 0.231        | 0.736 ± 0.292        | 0.731 ± 0.256        | 0.704 ± 0.279        | 0.727 ± 0.256        |
| Naive-ADDA                    | 0.491 ± 0.405        | 0.678 ± 0.266        | 0.693 ± 0.297        | 0.662 ± 0.265        | 0.693 ± 0.273        | 0.592 ± 0.306        |
| Realistic-Scaled              | <b>0.857 ± 0.184</b> | <b>0.853 ± 0.179</b> | <b>0.838 ± 0.221</b> | <b>0.818 ± 0.221</b> | 0.783 ± 0.262        | <b>0.823 ± 0.221</b> |
| Realistic-Cyc-Scaled          | 0.822 ± 0.213        | 0.794 ± 0.232        | 0.824 ± 0.225        | 0.789 ± 0.240        | <b>0.789 ± 0.241</b> | 0.812 ± 0.227        |

Gao, C., "SyntheX: Scaling Up Learning-based X-ray Image Analysis Through In Silico Experiments", *arXiv e-prints*, 2022. doi:10.48550/arXiv.2206.06127.

# Significance

- This paper demonstrate that **creating realistic simulated images** from human models **is a viable alternative and complement** to large-scale in situ data collection.
- It greatly **reduce the need of collecting huge amount of clinical data** in the training process of medical image analysis.
- Furtherly, the paradigm can be used to **generate reliable landmark detection result** intraoperatively and accurately, comparing to traditional, manually annotation process.

# Assessment

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## Pros:

- Contains a thorough and detailed description of testing methodology and analysis of the results.
- The code Dr. Gao provides is easy to integrate into other medical image process.

## Cons:

- Landmark detection is fundamentally imprecise, so we cannot simply rely on landmarks only to perform other tasks.

## Possible Future Work:

- Utilize and test the program results during the operation.
- Integrate the model into our 2D/3D registration process.

# Summary

- **Trained and evaluated** the deep learning models on **both realistic and synthetic data**.
- Demonstrated the feasibility of **training** the deep learning models to analyze X-ray images **using synthetic data**.
- Compared the **domain randomization method** and **other domain adaptation methods**.

Gaussian Noise Injection, Random Crop, etc.

CycleGAN, Adversarial Discriminative Domain Adaptation

## Conclusion:

SyntheX can significantly improve the performance of **deep learning models for X-ray image analysis**, especially in cases where **realistic X-ray images are limited or difficult to obtain**.

## Paper Selection

Paper 2: Robust Patella Motion Tracking using Intensity-based 2D-3D Registration on Dynamic Bi-plane Fluoroscopy: Towards Quantitative Assessment in MPFL reconstruction surgery

Otake, Yoshito; Esnault, Matthieu; Grupp, Robert; Kosugi, Shinichi; Sato, Yoshinobu

It presents a method for tracking of the kneecap during MPFL reconstruction surgery by applying an intensity-based 2D-3D registration technique to align 2D fluoroscopic images with CT Scans.

# Paper Selection

Paper 2: Robust Patella Motion Tracking using Intensity-based 2D-3D Registration on Dynamic Bi-plane Fluoroscopy: Towards Quantitative Assessment in MPFL reconstruction surgery

## Why do we choose this paper?

- Excellent example of intensity-based registration
- Solve the weakness of the SyntheX

# Background

- **MPFL** (medial patellofemoral ligament) reconstruction surgery is a surgical procedure that is performed to **treat patellar instability**
- **Bi-plane** fluoroscopic images are usually used in MPFL reconstruction surgery to get **patella tracking**.
- Motion tracking ensures that the graft is positioned correctly

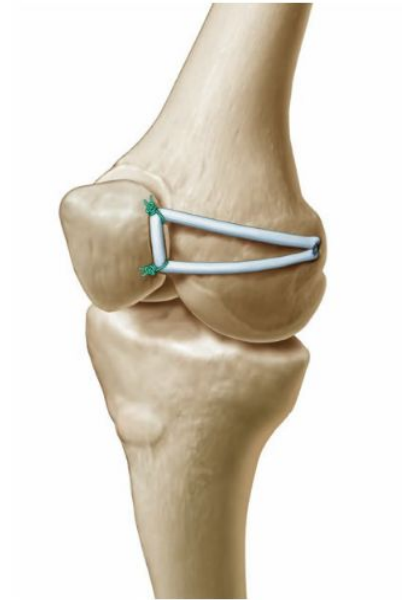


Figure 10.1 from [1]B. Ambrožič, S. Novakand M. Nabergoj, "Medial Patellofemoral Ligament Reconstruction Techniques", 2021, pp. 163–174. doi: 10.1007/978-3-030-57578-6\_10.

# Experiment Details - Methodology

- **Rough manual estimate** of the transformation for the registration of the first frame
- Apply the **covariance matrix adaptation Evolution strategy** optimization algorithm(CMA-ES) to generate transformation based on initial guess
- Compute DRRs of bone volume previously extracted from CT based on these transformation
- The quality of the registration is then assessed using **Gradient Correlation (GC)**

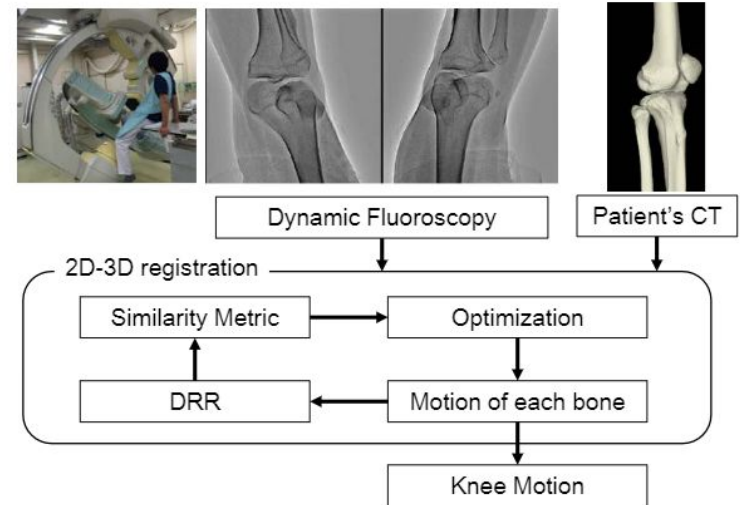


Figure1 from Y. Otake et al., "Robust patella motion tracking using intensity-based 2D-3D registration on dynamic bi-plane fluoroscopy: Toward quantitative assessment in MPFL reconstruction surgery,"Proc. SPIE, vol. 9786, 2016,Art. no. 97 860B

# Experiment Details

- Four registration approaches of femur, tibia-fibula, and patella:
  - Individual bone approach
  - Sequential bone approach
  - Simultaneous bone approach
  - Combination of the sequential and simultaneous approach
- Experiments with **simulated images**
- Experiments with **measured fluoroscopic images**

# Test results:

**Simulated images experiment results:** All femur and tibia-fibula registrations are successful for four approaches. Individual bone approach has **87%** success rate for patella registration, while others have **100%** success rate.

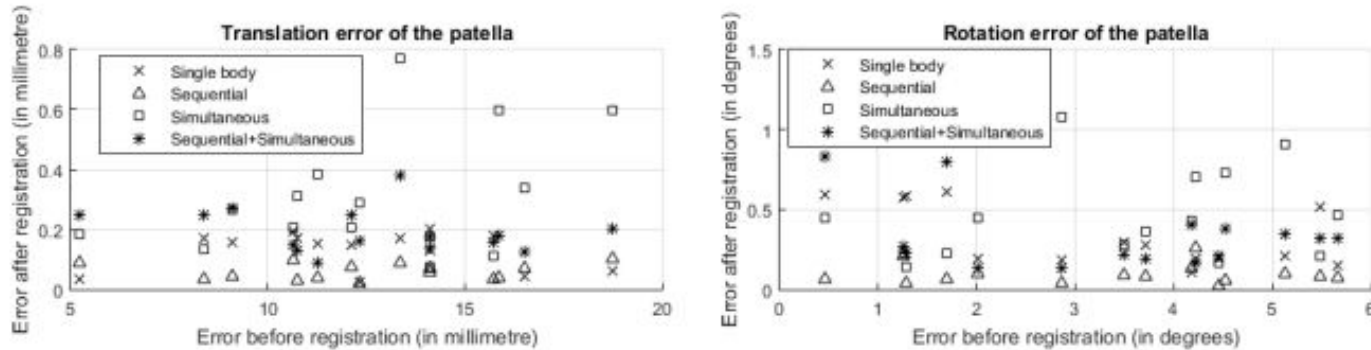
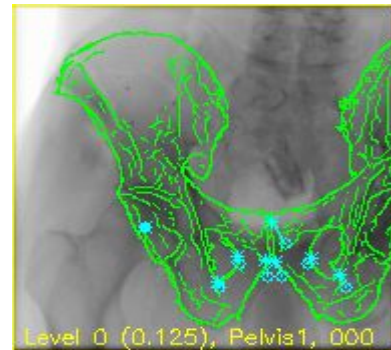


Figure from Y. Otake et al., "Robust patella motion tracking using intensity-based 2D-3D registration on dynamic bi-plane fluoroscopy: Toward quantitative assessment in MPFL reconstruction surgery," Proc. SPIE, vol. 9786, 2016, Art. no. 97 860B

**Measured fluoroscopic images experiment results:** All femur and tibia-fibula registrations are successful for four approaches. While for patella registration, four approaches exhibit **38%, 74% 70%, 68%** success rates respectively.

## Significance:

- Presents a novel method for tracking motion of the kneecap compared to low-resolution MRI method
- Sequential approach improved robustness significantly compared to the individual bone approach
- Address the weakness of synthex paper by combining landmark features and intensity feature.



<https://github.com/rg2/Regi2D3D-IPCAI2020>

# Assessment

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## Pros:

- Presents clear and precise workflow
- presents a thorough evaluation of the registration algorithm using quantitative metrics

## Cons:

- The study is limited to a small sample of patients
- Unclear about how the optimization algorithm affect the performance

# Summary

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- Propose a robust method to measure 3D motion of multiple rigid objects with high accuracy
- CMA-ES optimizer is used with GC evaluation for the registration
- Four approaches are implemented and compared

## Conclusion:

A robust, intensity-based 2D/3D registration on dynamics bi-plane fluoroscopy has a strong performance of motion tracking

# Reference

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- [1]. Gao, C., "SyntheX: Scaling Up Learning-based X-ray Image Analysis Through In Silico Experiments", *arXiv e-prints*, 2022. doi:10.48550/arXiv.2206.06127.
- [2]. Y. Otake et al., "Robust patella motion tracking using intensity-based 2D-3D registration on dynamic bi-plane fluoroscopy: Toward quantitative assessment in MPFL reconstruction surgery," *Proc. SPIE*, vol. 9786, 2016, Art. no. 97 860B
- [3]. Chen, Jieneng, et al. "Transunet: Transformers make strong encoders for medical image segmentation." *arXiv preprint arXiv:2102.04306* (2021).



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