

# Joint Track Machine Learning

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# Outline

## Aims

Aim 1 - Joint Track Machine Learning

Aim 2 - Overcoming Single-Plane Limitations

Aim 3 - Pilot Human Study

Aim 4 - Standardized Kinematics Exam

Aim 5 - Joint Track Auto Toolkit

## References

## Acknowledgments

I would like to thank the McJunkin Family Charitable Foundation for their generous grant that supports this work.

# The Problem

- By 2030, roughly 3.5 million Total Knee Arthroplasty (TKA) will be performed in the US [15].
- 20% of patients receiving TKA are dissatisfied.
  - Instability, pain, unnatural [14, 17, 18].
- No reliable method of clinically assessing and quantifying joint dynamics.
  - Human supervision
  - Time consuming
  - Specialized equipment



# Our Proposition

Orthopaedic surgeons and clinicians would readily adopt a **practical** and **inexpensive** technology that allows them to **measure** a patient's knee kinematics during **activities of daily living**.

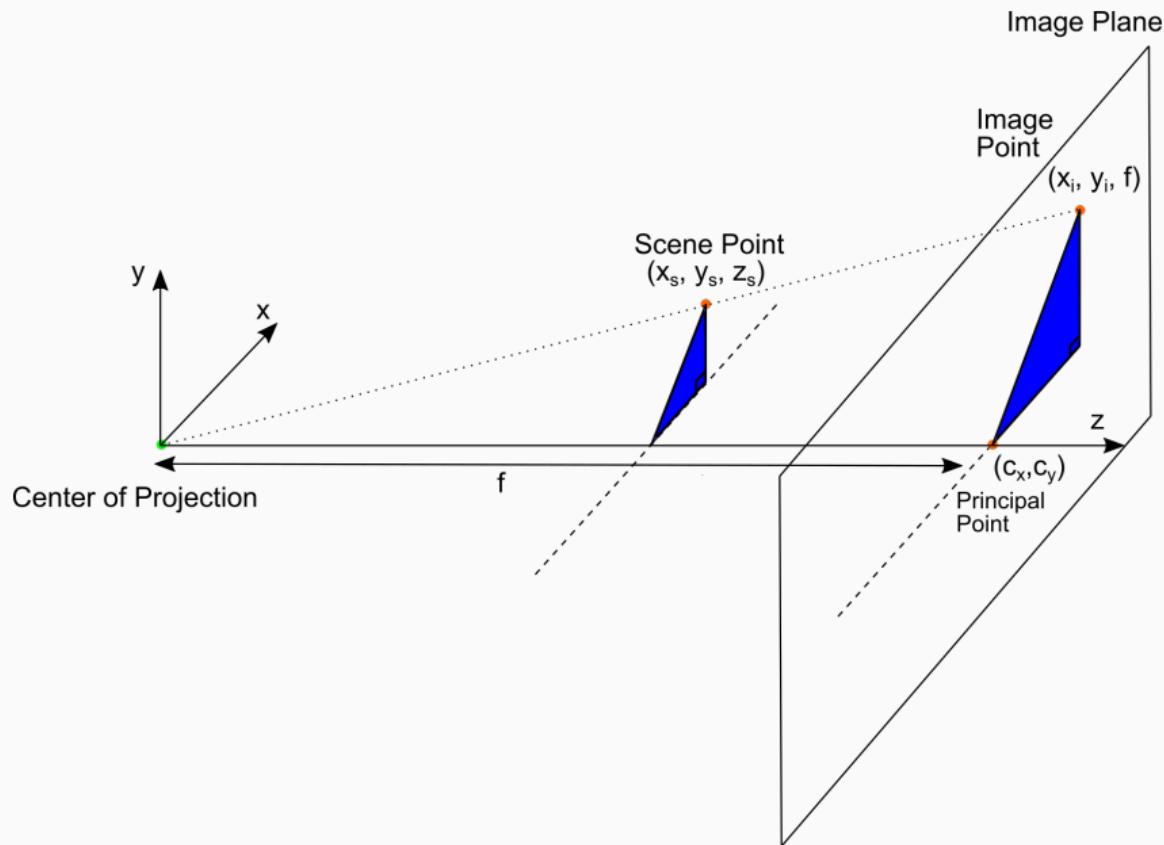


# Constraints

- It must fit within a **standard clinical workflow**
- The technology must utilize equipment **commonly found in hospitals**
- There must not be significant **human supervision** nor interaction to generate an examination report.

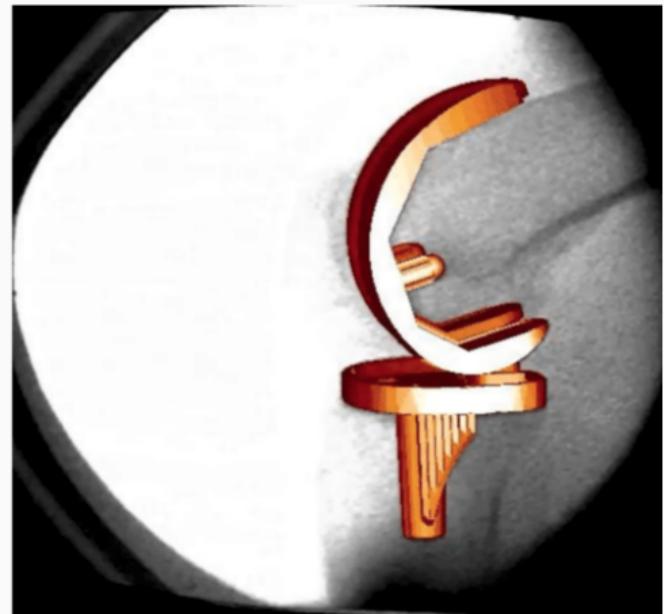


## Background - Projective Geometry



## Background - Model-Image Registration

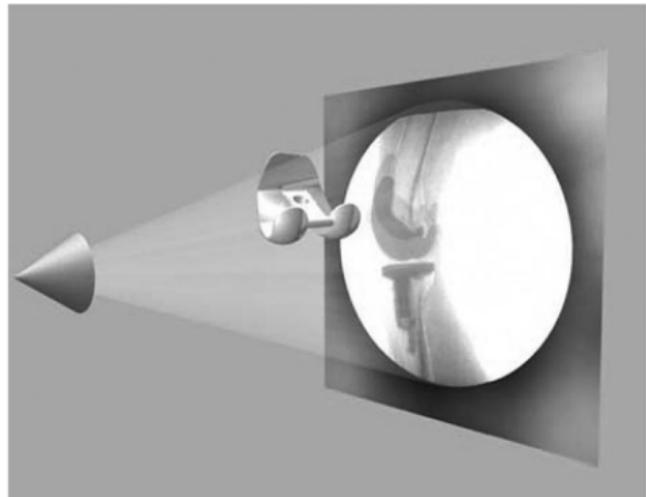
If we know the projective parameters of the fluoroscopy machine, can we tinker with  $T_{implant}^{cam}$  so that our virtual projection matches the fluoroscopic image?



From [11]

## Background - Model-Image Registration

If we know the projective parameters of the fluoroscopy machine, can we tinker with  $T_{implant}^{cam}$  so that our virtual projection matches the fluoroscopic image?



From [11]

## Historical Overview

Many different approaches have attempted to solve the model-image registration problem.

- Pre-computed projections
- Skin-mounted motion Capture
- Biplane Imaging
- Iterative Projections
- Roentgen Stereophotogrammetry

# Pre-Computed Projections

- Saving space and memory by pre-computing as much as possible.
- Pre-computed distance maps [34, 6].
- Pre-computed shape libraries [7]

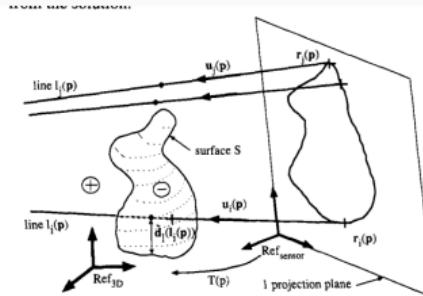
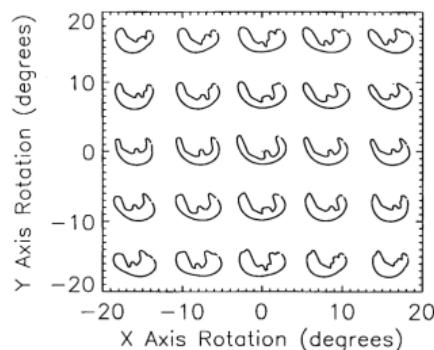


Fig. 2. Projection line to surface distance computation.

From [6]



From [7]

# Limitations of Pre-Computed Projections

- Requires an accurate contour from the input image in order to perform calculations.
  - Human supervision for isolated contour
  - Inaccuracy with naive edge detection

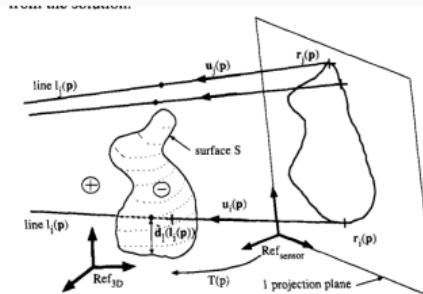
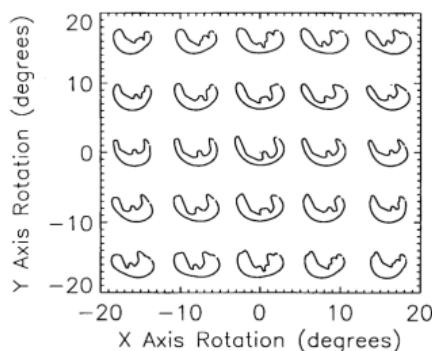


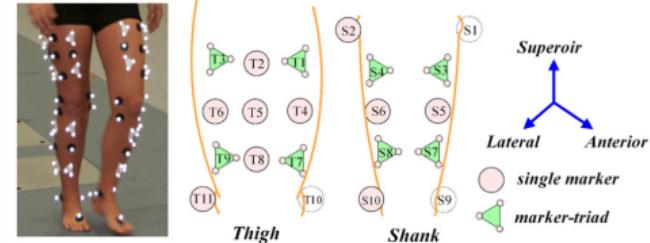
Fig. 2. Projection line to surface distance computation.

From [6]



From [7]

# Motion Capture (MoCap)



From [16]

- Can measure motion of MoCap beads very accurately.
- Skin-mounted [16, 19, 21].
- Bone pins [5].



From [5]

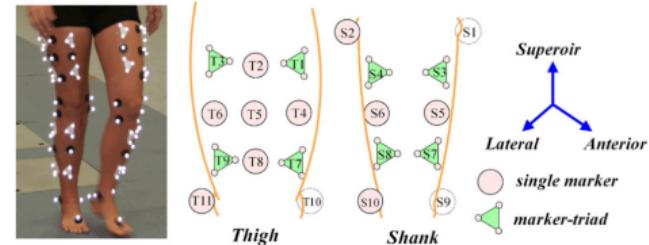
# Limitations of Motion Capture

## Skin Mounted

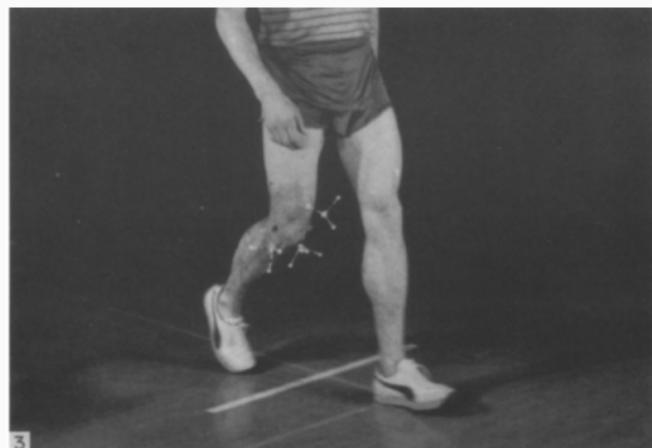
- Doesn't accurately describe underlying skeletal motion with clinical accuracy [16, 19, 21].

## Bone Pins

- Any volunteers?



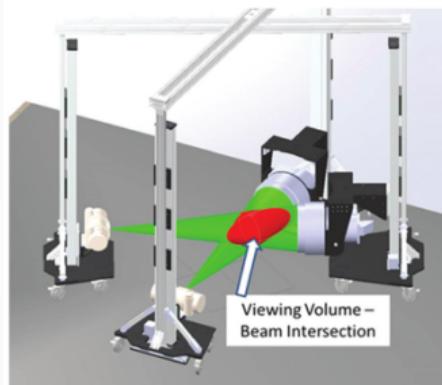
From [16]



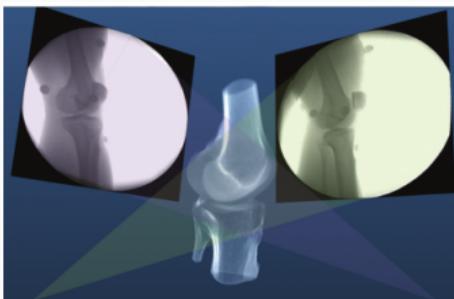
From [5]

# Biplane Imaging

- Utilizes multiple cameras to resolve 3D position and orientation[20, 29].
  - Highly accurate.
  - Gold Standard.

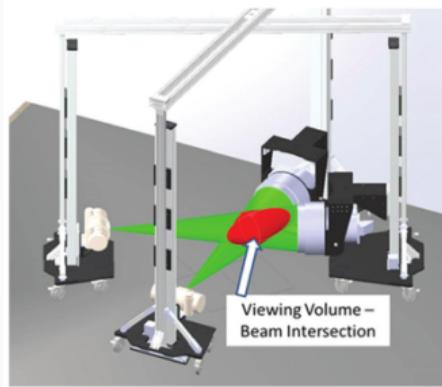


Both from [20]

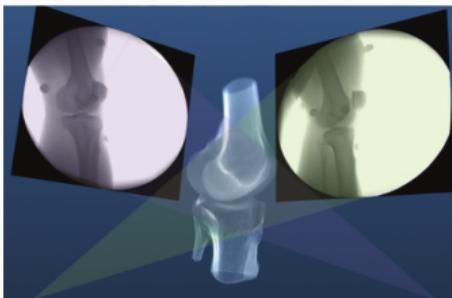


# Limitations of Biplane Imaging

- Not many hospitals have biplane fluoroscopy setups.
- Clinically impractical

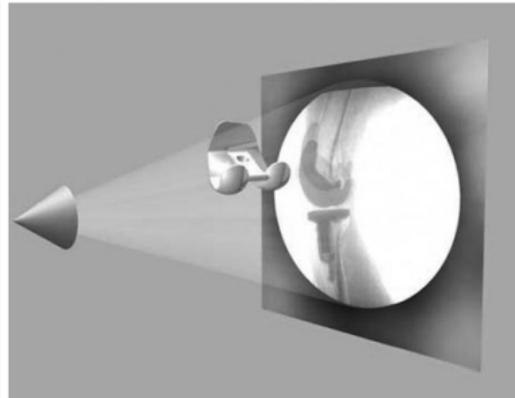


Both from [20]



# Iterative Projections

- Take advantage of modern computational graphics pipelines to quickly perform projection matching.
  - Image/Intensity similarity metrics [11]
  - Feature/Contour similarity metrics [24]



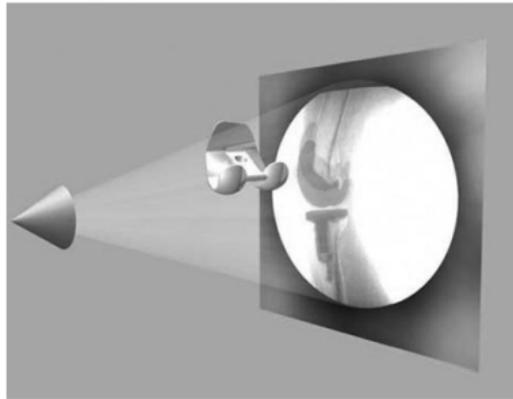
From [11]



From [24]

# Limitations of (historic) Iterative Projection Methods

- Requires human supervision for:
  - Pose initialization
  - Escaping local minima
  - Implant detection
- Chaotic and Noisy objective function



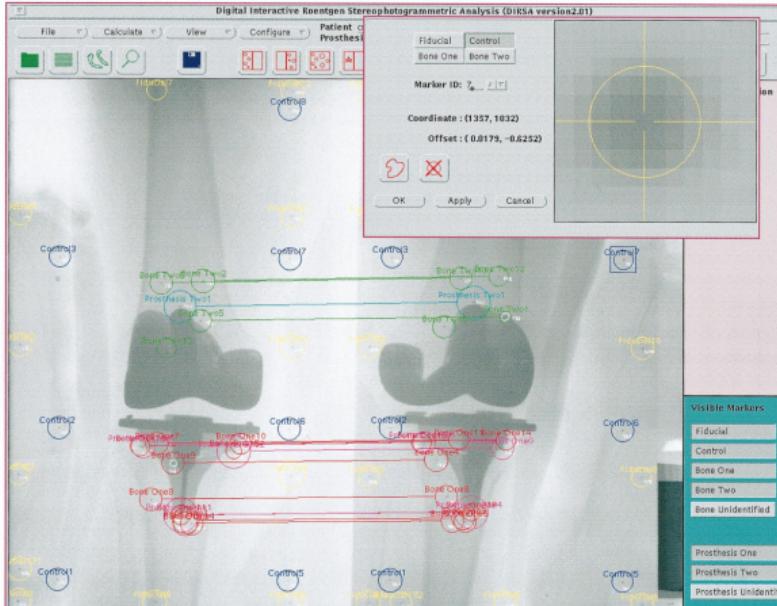
From [11]



From [24]

# Roentgen Stereophotogrammetry (RSA)

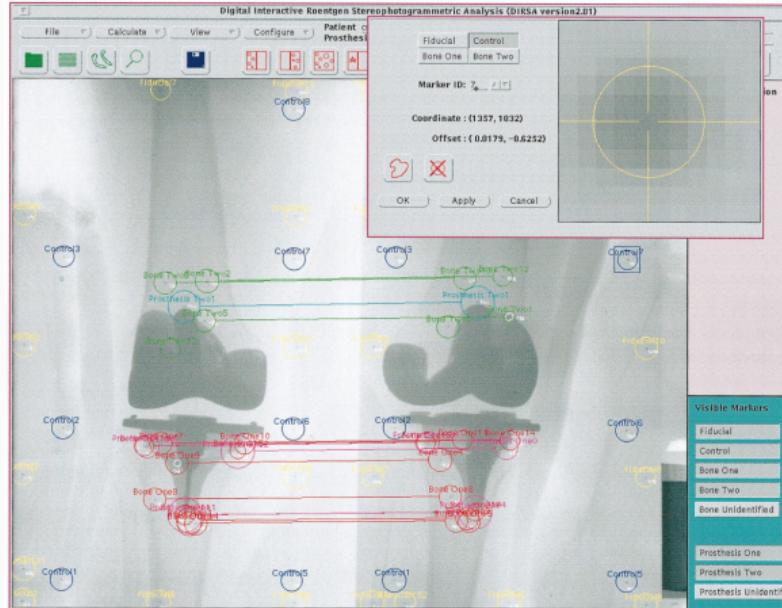
- Uses implanted tantalum beads for motion tracking [10, 4]
- Extremely accurate [12, 13]
- Gold standard Measurement [33]



From [10]

# Limitations of RSA

- Involves additional surgical procedures for inserting tantalum beads.
- Human supervision
- Bi-plane imaging



From [10]

## Aims

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# Aims

## Aims 1/2

Joint Track Machine

Learning and Overcoming

Single-Plane Limitations

## Aim 3/4

Pilot Trials and

Standardized Kinematics

Exam

## Aim 5

Joint Track Auto Toolkit

## Aims

Aim 1 - Joint Track Machine Learning

Aim 2 - Overcoming Single-Plane Limitations

Aim 3 - Pilot Human Study

Aim 4 - Standardized Kinematics Exam

Aim 5 - Joint Track Auto Toolkit

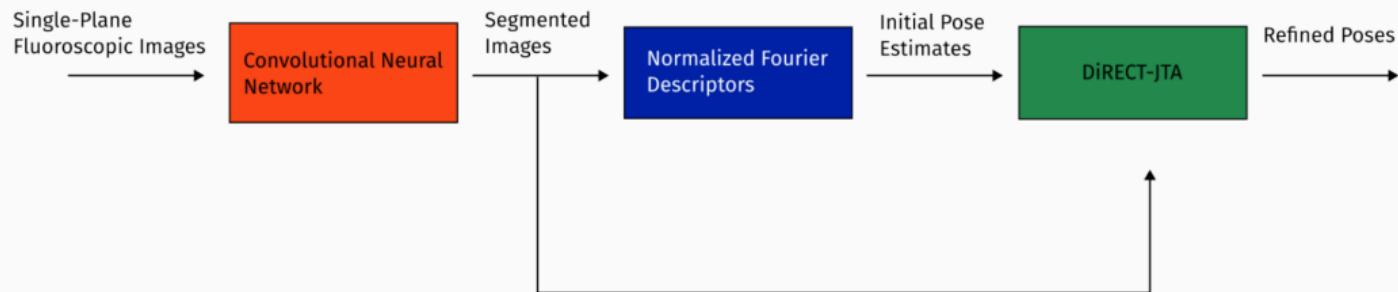
## References

# Goal

Demonstrate the feasibility of a fully autonomous, model-image registration pipeline.

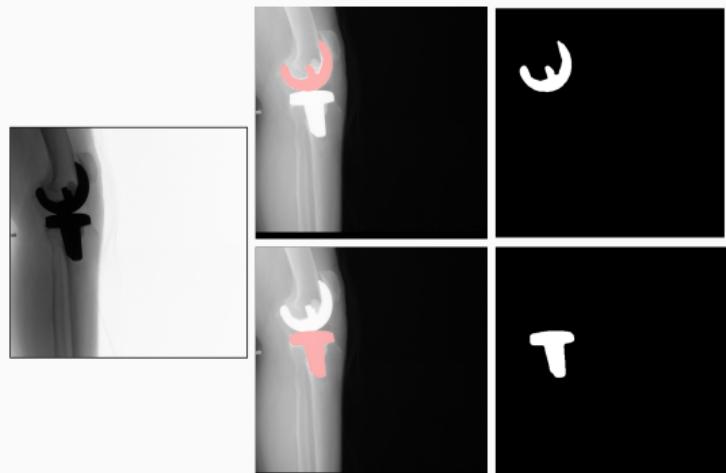
# Method

- Three-tiered approach
  - Convolutional Neural networks (CNN) for autonomous implant detection
  - Normalized Fourier Descriptor shape libraries
  - Robust contour-based global optimization scheme



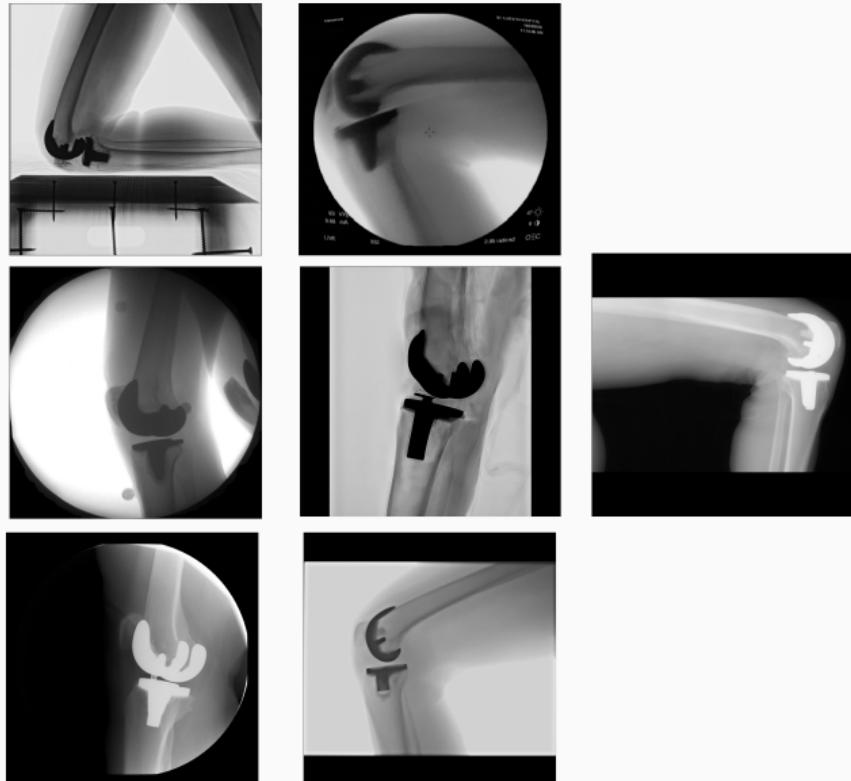
# Autonomous Implant Detection Using Convolutional Neural Networks

- 2 CNNs
  - Femoral and Tibial implants
- High Resolution Network [27]



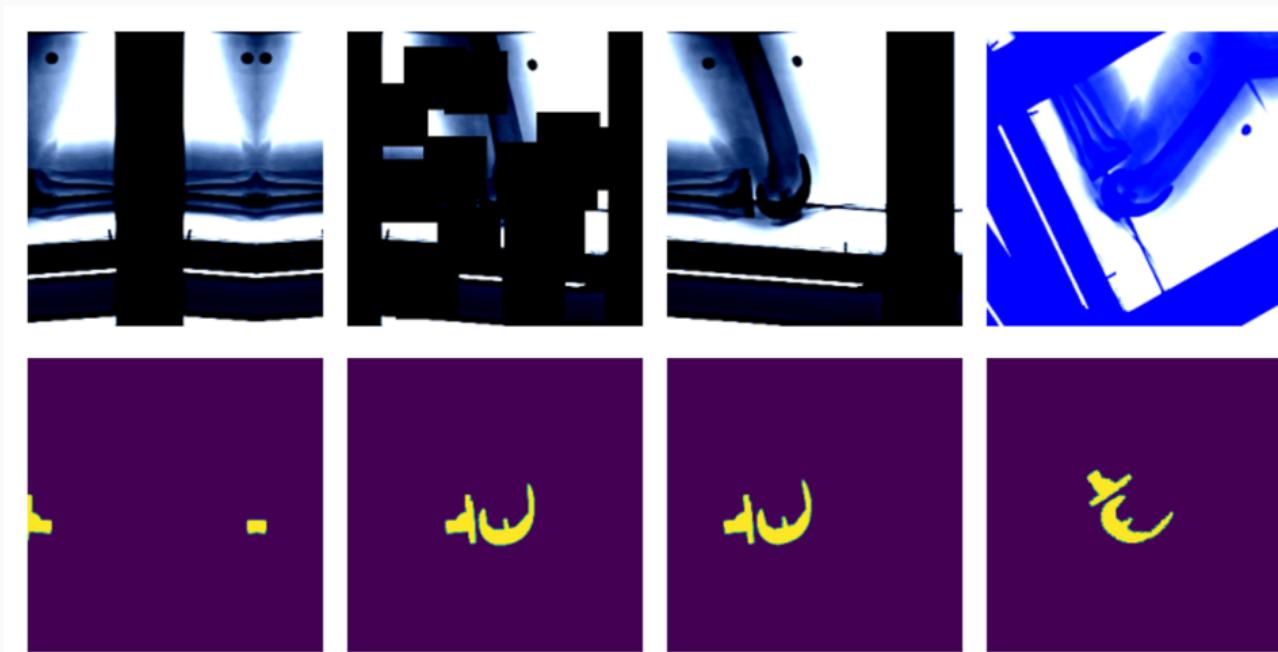
# Neural Network Data

- ~8000 images
  - 7 TKA kinematics studies
    - 71 subjects
    - 7 implant manufacturers
    - 36 distinct implants
    - Squat, lunge, kneel, stair ascent



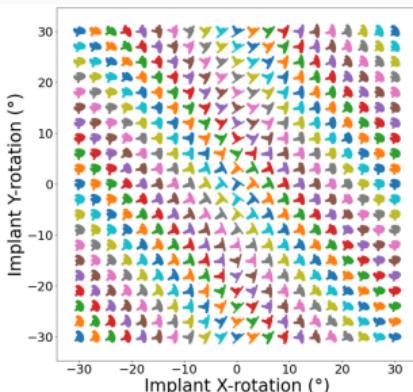
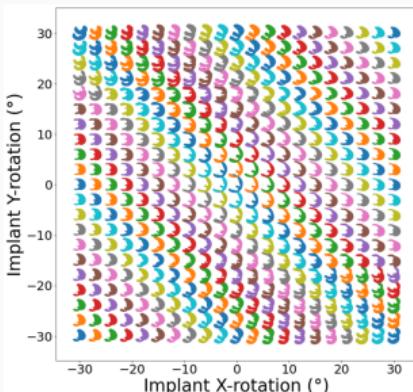
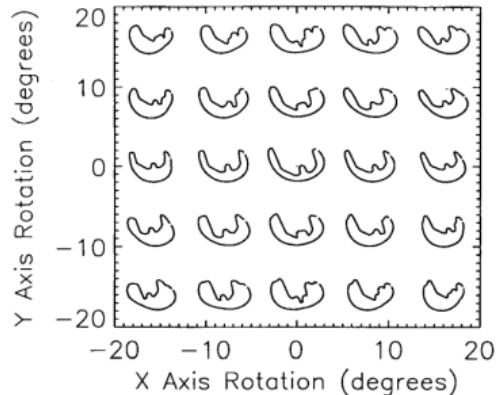
# Neural Network Robustness

- Additional augmentations introduced during training [25].



# Normalized Fourier Descriptor Shape Libraries

- Pose initialization using segmentation output.
- $\pm 30^\circ$  library span at  $3^\circ$  increments.



# Pose Refinement Using Global Optimization

- Two main features
  - Objective function
  - Optimization routine

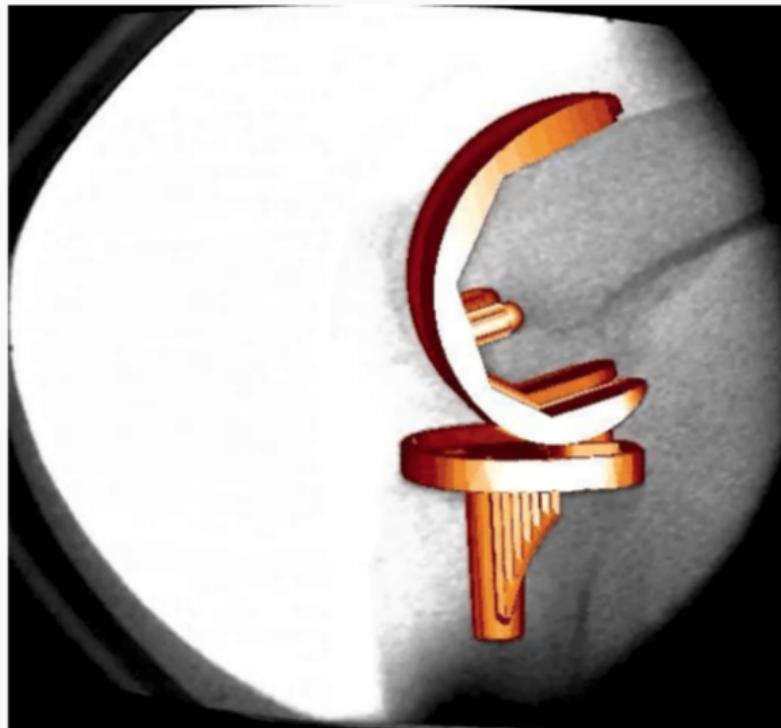
$$\underset{x}{\operatorname{argmin}} \{f(x) : x \in \Omega\}$$

## Contour-based Objective Function

- With accurate projection, contours provide a strong heuristic for orientation.
- Overlapping pixels between CNN segmentation and projected implant.
  - $L_1$  norm has quick parallel computation.

$$J = \sum_{i \in H} \sum_{j \in W} |I_{ij} - P_{ij}| = L_1(I, P)$$

- Sensitive to minor perturbations



## Improving Robustness

- Dilation decreases sensitivity to perturbations.
- Multi-stage optimization can reduce dilation back to original edges.

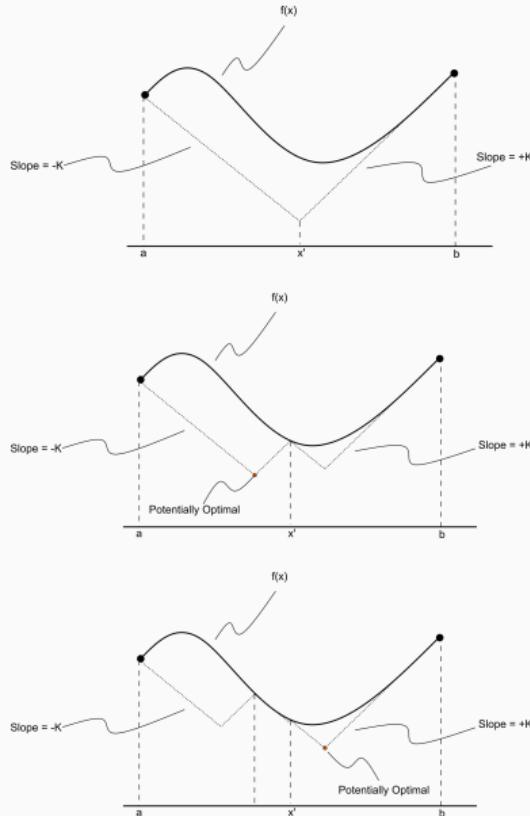


## Optimization Routine

- No analytic form of the objective function exists, it **must** be sampled at points of interest.
  - Black Box Optimization [22, 28]

# Lipschitzian Optimization

- Robust, global, black-box optimization routine if Lipschitz constant ( $K$ ) is known [2].
- Lipschitz constant bounds the rate of change of a function.
- What if you don't know the Lipschitz constant?

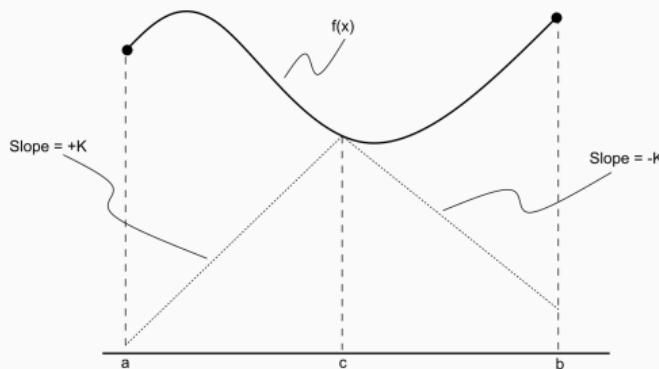


# Lipschitzian Optimization without the Lipschitz Constant

## Lipschitzian Optimization Without the Lipschitz Constant

D. R. JONES,<sup>1</sup> C. D. PERTTUNEN,<sup>2</sup> AND B. E. STUCKMAN<sup>3</sup>

- Sample end-points instead of intersecting lines.
- Potentially optimal regions based on value at center and total size.
  - Trisect potentially optimal regions and re-sample centers



# Trisecting Region

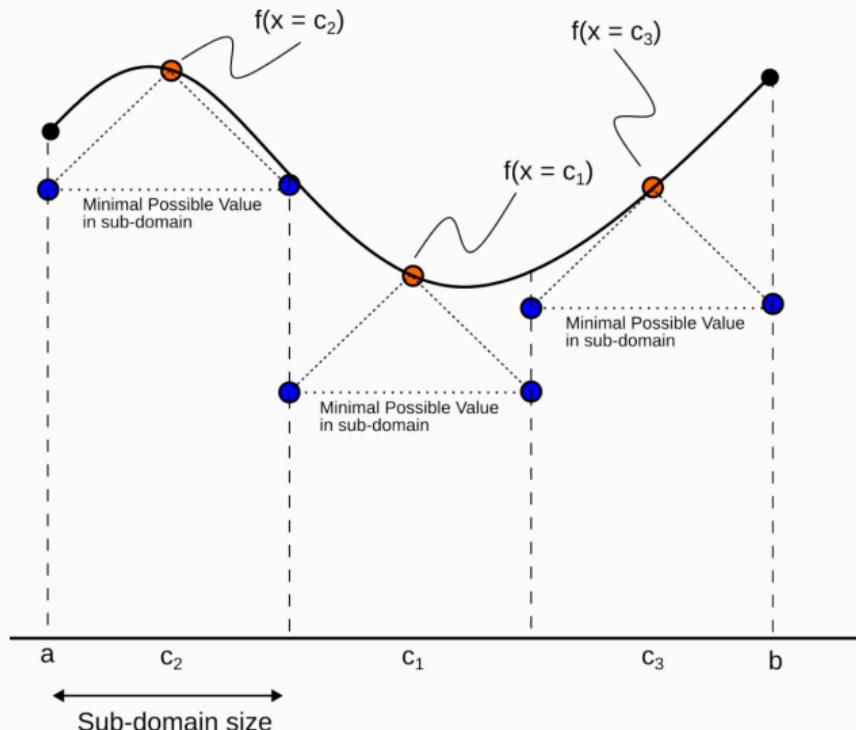
$$\begin{bmatrix} f(x = c_1) & d(c_1) \\ f(x = c_2) & d(c_2) \\ \vdots & \vdots \\ f(x = c_N) & d(c_N) \end{bmatrix}$$

Where

$f(x = c_i) \equiv$  Sampled function value

$d(c_i) \equiv$  Sub-domain size

for  $i \in [1, N]$



## Another Iteration

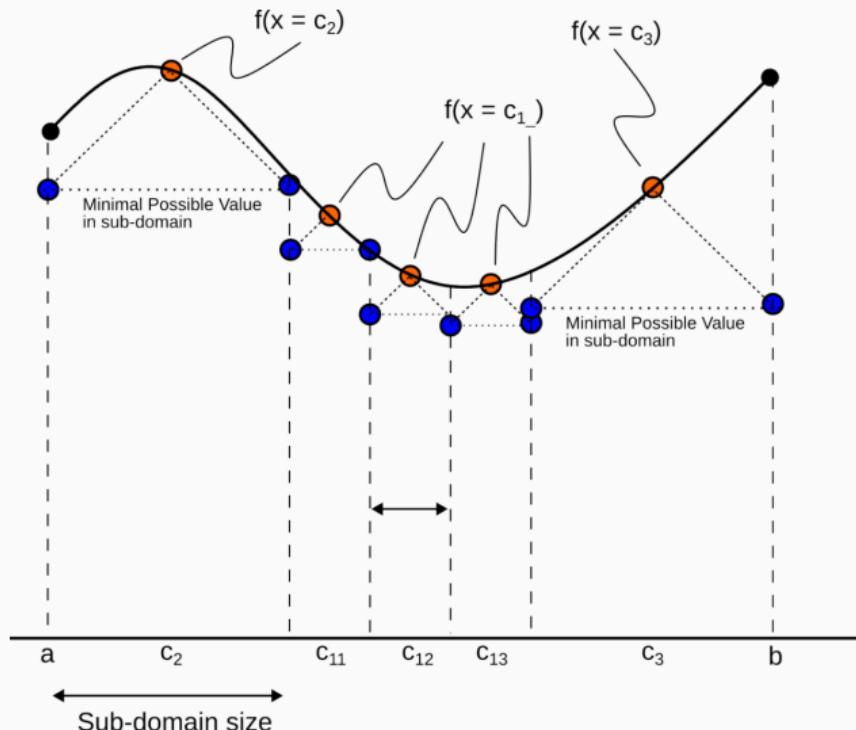
$$\begin{bmatrix} f(x = c_1) & d(c_1) \\ f(x = c_2) & d(c_2) \\ \vdots & \vdots \\ f(x = c_N) & d(c_N) \end{bmatrix}$$

Where

$f(x = c_i) \equiv$  Sampled function value

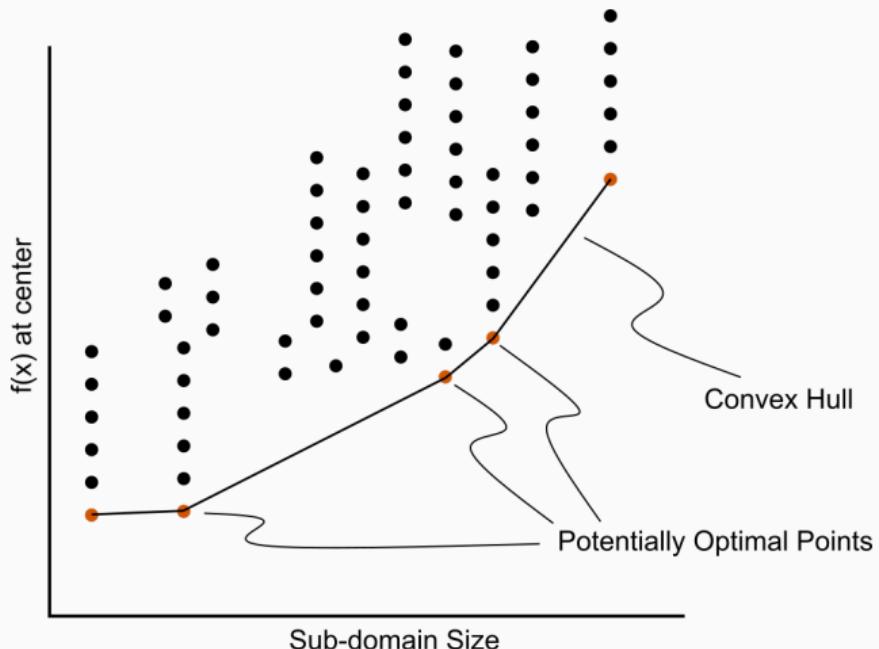
$d(c_i) \equiv$  Sub-domain size

for  $i \in [1, N]$



# Determining Potentially Optimal Regions

- Convex hull [1, 3, 9, 8] of region size vs. center value



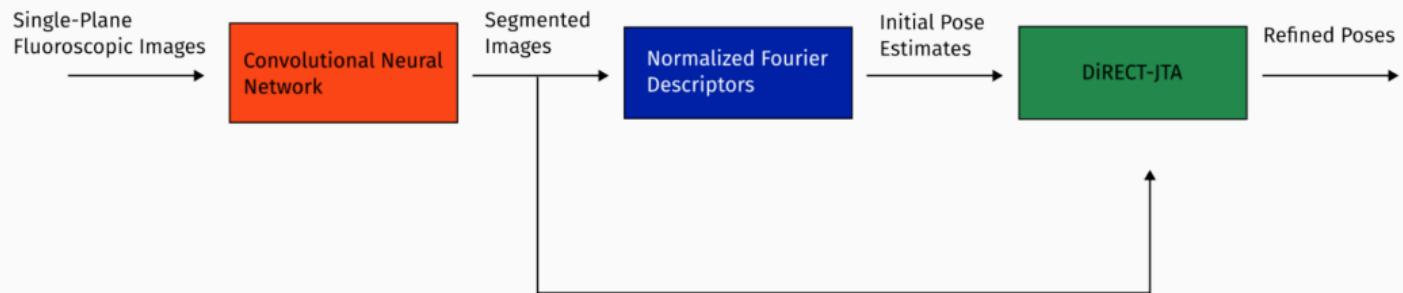
# DiRECT for Joint Track Machine Learning

- Search region is along all 6 degrees of freedom.
  - Normalize to [0, 1].
- Three stages, each with decreasing levels of dilation.
  - Iteration budget for each stage.

Stage	Budget [Iterations]	Search Range [mm,deg]	Dilation (pixels)
“Tree”	~20,000	±45	5
“Branch”	~20,000	±25	3
“Leaf”	~10,000	±100 ( $z_{trans}$ ) / ±3 ( <i>else</i> )	1

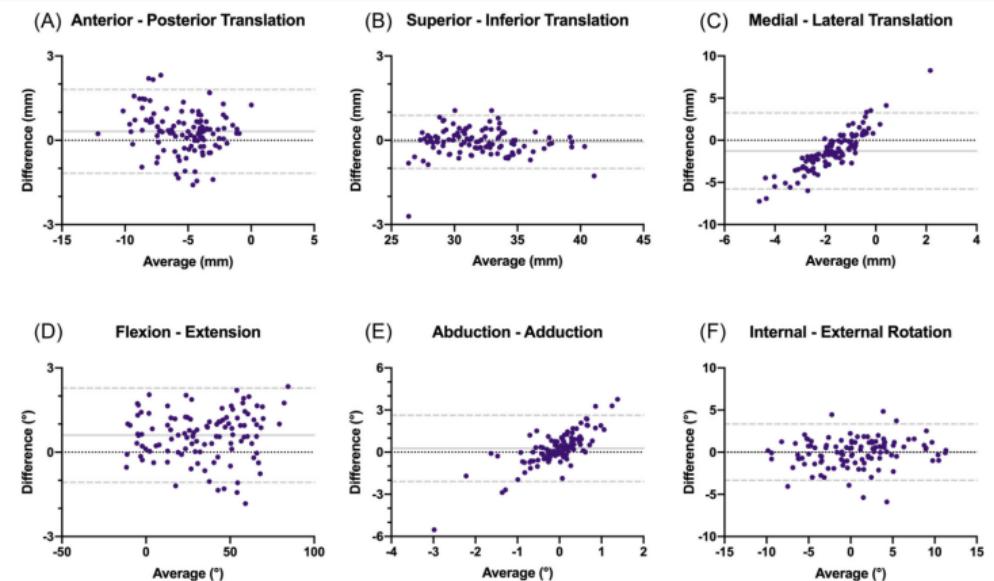
# Testing Performance

Now that we have our refined poses, how well does our system perform?



# Validation

- Independent research group using Model-Based RSA.
- Determine the level of concordance between the two measurement systems
  - Bland-Altman Plots
- Achieved clinically acceptable accuracy [33, 32].
- Highly repeatable



## Awards

The work presented in this aim won the HAP Paul Award for Best Paper from the International Society for Technology in Arthroplasty's 2022 Annual Meeting.



## Aims

Aim 1 - Joint Track Machine Learning

Aim 2 - Overcoming Single-Plane Limitations

Aim 3 - Pilot Human Study

Aim 4 - Standardized Kinematics Exam

Aim 5 - Joint Track Auto Toolkit

## References

## Goal

- The goal of this aim is to validate and test methods that can overcome single-plane limitations for model-image registration.
  - Out-of-plane (OOP) Translation
  - Symmetry Traps

## Translation

- Depth perception is lost when using a single camera.
- Utilize a virtual “spring” to constrain relative OOP translation between implant components.

$$J = \alpha L_1(I, P) + \beta ML(Fem, Tib)$$

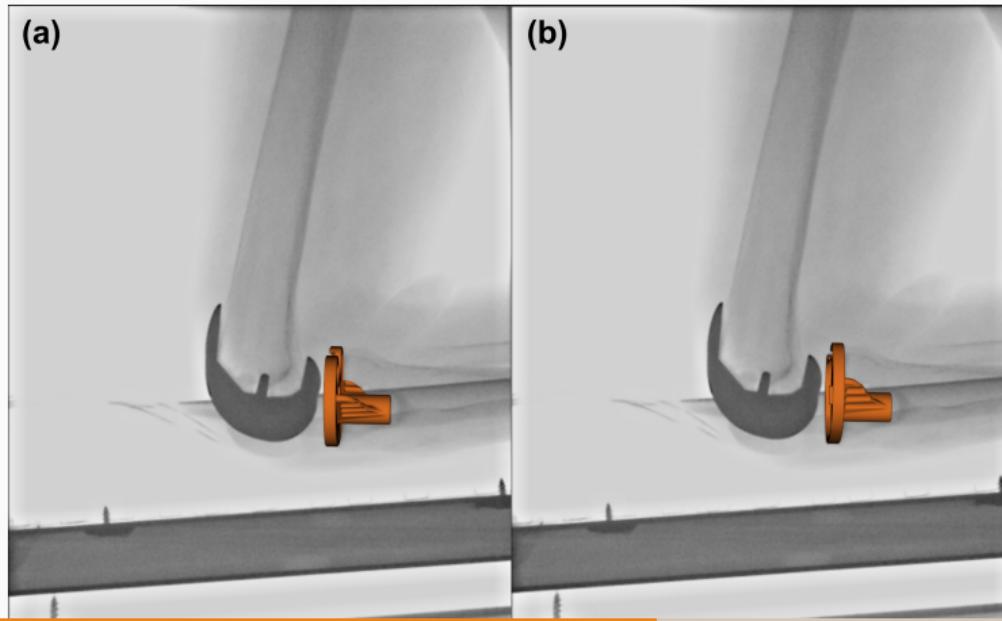
Where

$ML \equiv$  Relative mediolateral translation

## Symmetry Traps

With a symmetric tibial implant, the contour is not always a perfect heuristic for true pose. Human operators typically utilize relative varus-valgus to determine correct pose.

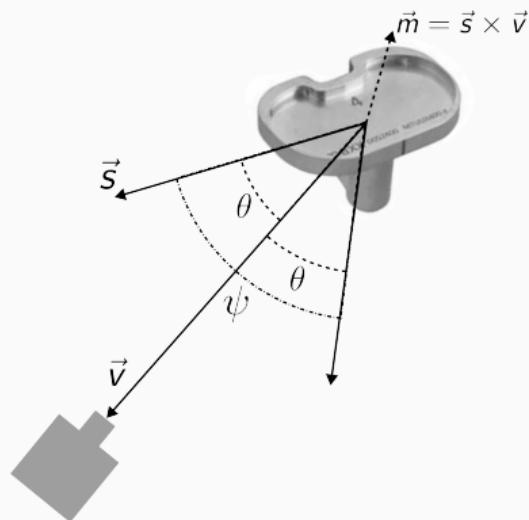
Found “ambiguous zone” within  $3^\circ$  of pure lateral pose with high propensity for symmetry traps [32].



## Solving the Symmetric Pose

Algorithm devised to “flip” pose into symmetric counterpart.

1. Determine viewing ray from camera to implant centroid, denote  $\vec{v}$ , normalize.
2. Denote symmetric-plane normal vector  $\vec{s}$ , normalize.
3. Measure relative “off-lateral” orientation of implant,  
$$\cos(\theta) = \frac{\vec{v} \cdot \vec{s}}{||\vec{v}|| ||\vec{s}||}$$
4. Apply body-centered rotation to implant about  $\vec{m} = \vec{s} \times \vec{v}$  by  $\psi = 2\theta$ .



## Four Approaches

- Virtual ligaments
- Binary selection between two poses
- Bland-Altman Calibration Constant
- Fully Connected Network

## Virtual Ligaments

$$J = \alpha L_1(I, P) + \beta ML(Fem, Tib) + \gamma VV(Fem, Tib)$$

Where

$VV \equiv$  Relative Varus-Valgus rotation

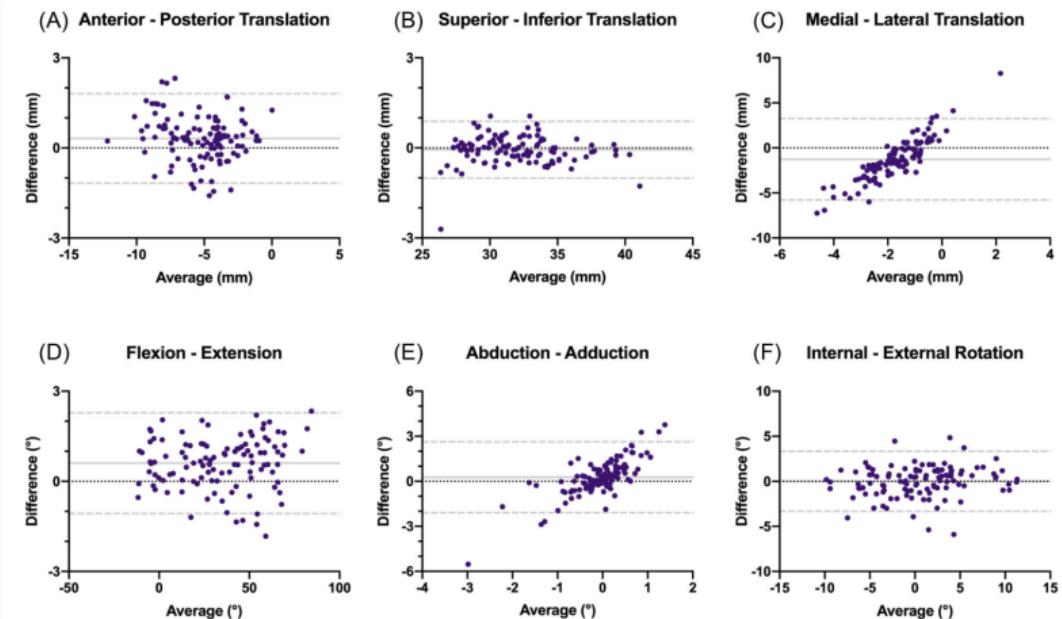
## Binary Selection

1. Determine optimized pose using  $L_1 + ML$
2. Calculate symmetric pose.
3. Pick pose with lower relative VV

This method can simplify the selection criteria (one fewer hyperparameter).

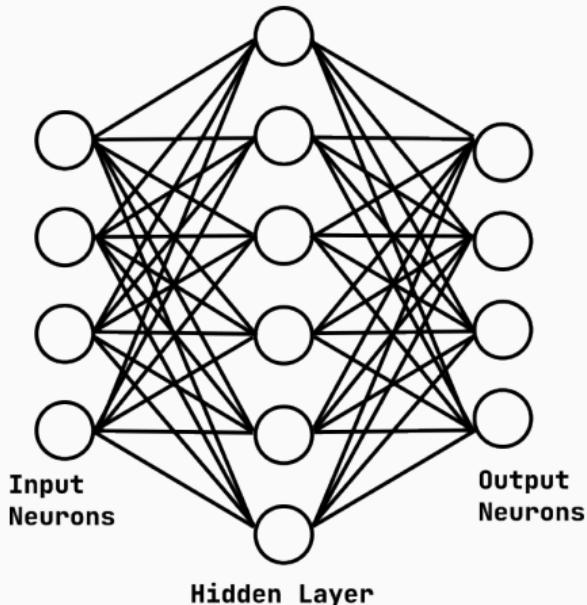
# Bland-Altman Calibration Constant

- Utilizing Bland-Altmann plots from gold-standard kinematics, create a “correction constant” for relative varus/valgus (ad/abduction) angles.
- Notice linear trend in BA plots.



# Fully Connected Network

- Encode symmetric pose calculation into FCN.
- Feed femoral and tibial **pose** into network.
  - “Keep” or “Switch”
- Could incorporate categorical features as well
  - Weightbearing vs non-weightbearing
  - Activity (walking, stair, lunge, etc)



## Timeline

- All kinematics data has already been collected.
- Completed Methods
  - Virtual Ligaments
- In Progress
  - Binary Selection
- Pending Methods
  - Bland-Altman Calibration
  - Fully Connected Network

Journal paper will be ready for submission by June.

## Aims

Aim 1 - Joint Track Machine Learning

Aim 2 - Overcoming Single-Plane Limitations

**Aim 3 - Pilot Human Study**

Aim 4 - Standardized Kinematics Exam

Aim 5 - Joint Track Auto Toolkit

## References

# Goal

No kinematics studies have exclusively utilized Joint Track Machine Learning; let's be the first.

What are we measuring?

- Kinematics
- Time to full examination report
  - Time/frame
  - Usage hiccups
  - Symmetry traps

## Methods

- 20-30 patients
- ~Dozen activities with fluoroscopic machine
  - Weightbearing and Non-weightbearing
  - Static and Dynamic

IRB approval ~4 months out.

## Aims

Aim 1 - Joint Track Machine Learning

Aim 2 - Overcoming Single-Plane Limitations

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## References

## Goal

Establish a “standard kinematics exam” by determining the most statistically and anatomically relevant fluoroscopic image(s) to capture during a clinical visit.

## Motivation

- We have standardized pain/outcome scores
  - KOOS, KSS, FJS, etc..
- No standardized kinematics examination
  - Per-study differences
  - No reason to standardize

Autonomous kinematics measurements allow researchers to spend more time asking and answering questions rather than fiddling with annoying software.

## Method

- Use images and kinematics from Aim 3.
- Utilize statistical methods to determine covariance and causal/corollary relationships.
  - Clustering
  - Transformers [26, 23, 31, 30] (“translating” movements into outcomes and other movements)

## Aims

Aim 1 - Joint Track Machine Learning

Aim 2 - Overcoming Single-Plane Limitations

Aim 3 - Pilot Human Study

Aim 4 - Standardized Kinematics Exam

Aim 5 - Joint Track Auto Toolkit

## References

## Joint Track Auto Toolkit (JTAT)

Create a freely available Python library that allows other researchers to utilize JTML's model-image registration framework. Extra emphasis will be placed on extensibility to allow other researchers to compose their own registration pipelines.

## Presentations

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- [1] Scott Banks, Andrew James Jensen, and Paris Flood. *In Regione Caecorum Rex Est Lucus - Towards Routine Clinical Examinations of Joint Kinematics.* International Radiostereometry Society Meeting, 2019.
- [2] Paris Flood, Andrew Jensen, and Scott Banks. *Towards Practical Clinical Examination of 3D Joint Kinematics Using Machine Learning.* International Society for Technology in Arthroplasty, 2019.
- [3] Andrew Jensen, Yifei Dai, and Andrea Gardner. *Impact of Sagittal Resection Variability on Implant Fit during Partial Knee Arthroplasty.* Podium. Phoenix, AZ, 2020.

## Presentations ii

- [4] Andrew Jensen et al. *Comparison of Clinical and Computational Implant Fit Analysis in Partial Knee Arthroplasty*. Podium. Orthopaedic Research Society, 2020.
- [5] Andrew Jensen et al. *Towards Routine Clinical Examination of 3D Joint Kinematics*. Korean Orthopaedic Association, 2020.
- [6] Yifei Dai et al. *Comparative Analysis of Fixation Structure Design on the Primary Stability of Cementless TKA during Walking*. Orthopaedic Research Society, 2021.
- [7] Yifei Dai et al. *Impact of Fixation Components on Primary Stability of Cementless TKA during Walking*. Podium. Orthopaedic Research Society, 2021.

## Presentations iii

- [8] Andrew Jensen et al. *An Autonomous Method for Extracting Joint Kinematics from Single-Plane Fluoroscopy*. International Radiostereometry Society, 2021.
- [9] Andrew James Jensen et al. *An Autonomous Method for Extracting 3D Knee Replacement Kinematics from Dynamic Single Plane Fluoroscopic Images*. International Society for Technology in Arthroplasty: Emerging Technologies, 2021.
- [10] Jacob Griffith et al. *Automated Segmentation and Grading of Rodent Knee OA Histology Using Convolutional Neural Networks*. Poster. Orthopaedic Research Society, 2022.
- [11] Andrew Jensen, Lindsey Palm, and Scott Banks. *Autonomous Measurement of 3D TKA Kinematics from Dynamic Single-Plane Fluoroscopic Images*. Podium. Orthopaedic Research Society, 2022.

- [12] Andrew Jensen. *Deep Learning for Image Processing in Orthopaedics.*  
Virtual Scientific Session. Orthopaedic Research Society, 2023.

## Publications

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- [1] William Burton et al. “**Automatic Tracking of Healthy Joint Kinematics from Stereo-Radiography Sequences.**”. In: *Computers in Biology and Medicine* (2021). DOI: 10.1016/j.combiomed.2021.104945.
- [2] Andrew Jensen et al. “**Joint Track Machine Learning: An Autonomous Method for Measuring 6DOF TKA Kinematics from Single-Plane x-Ray Images**”. In: *arXiv:2205.00057 [q-bio]* (Apr. 2022). arXiv: 2205.00057 [q-bio].
- [3] Jordan S. Broberg et al. “**Validation of a Machine Learning Technique for Segmentation and Pose Estimation in Single Plane Fluoroscopy**”. In: *Journal of Orthopaedic Research* (Feb. 2023), jor.25518. ISSN: 0736-0266, 1554-527X. DOI: 10.1002/jor.25518.

## Timeline

Date(s)	Event
2015-2019	Mech. Eng. B.S, Magna Cum Laude, UF
April 2019 - April 2020	Internship at Exactech
April 2020	Started in Miller Lab
August 2020	Officially Started PhD at UF
November 2021	Best Presentation Award at ISTA: Emerging Technologies
April 2022	Submitted JTML for HAP Paul Award
September 2022	HAP Paul Award at ISTA 2022
June 2023	Single-plane limitations paper submitted
July 2023	Est. IRB Approval
August 2023	v1.0 JTAT
December 2023 ~ May 2024	Patient Data Fully Collected (Aims 3/4)
August 2024	Papers for Aims 3/4 Submitted
December 2024 - April 2025	Est. Graduation

Thank you!

Thanks for listening!!

## References

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## References

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- [1] R.L. Graham. “An Efficient Algorithm for Determining the Convex Hull of a Finite Planar Set”. In: *Information Processing Letters* 1.4 (June 1972), pp. 132–133. ISSN: 00200190. DOI: 10.1016/0020-0190(72)90045-2.
- [2] Bruno O. Shubert. “A Sequential Method Seeking the Global Maximum of a Function”. In: *SIAM Journal on Numerical Analysis* 9.3 (1972), pp. 379–388. DOI: 10.1137/0709036. eprint: <https://doi.org/10.1137/0709036>.
- [3] R A Jarvis. “On the Identification of the Convex Hull of a Finite Set of Points in the Plane”. In: (1973).
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