

Joint Track Machine Learning

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March 9, 2023

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**.

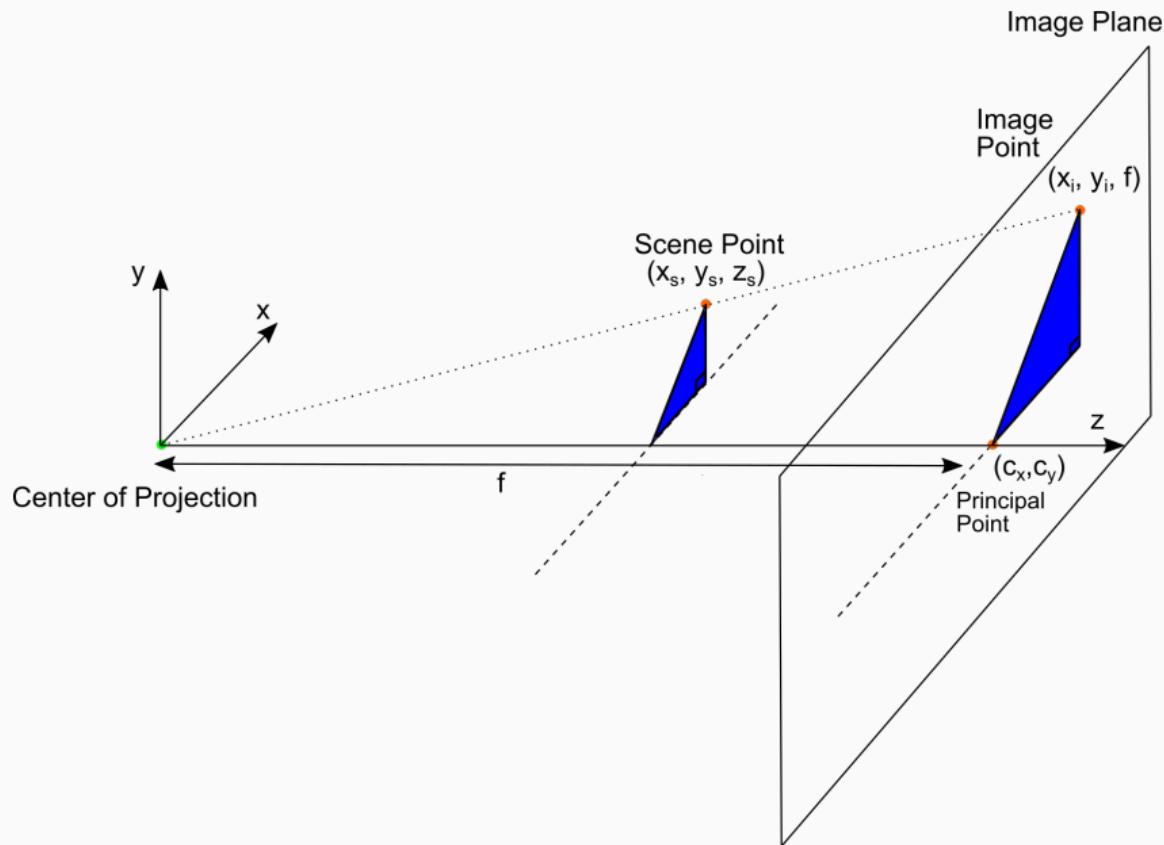


Constraints

- 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.

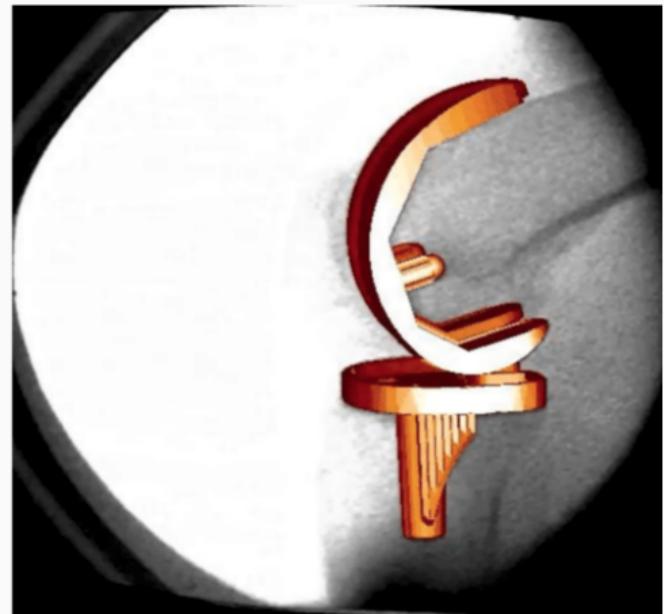


Background - Projective Geometry



Background - Model-Image Registration

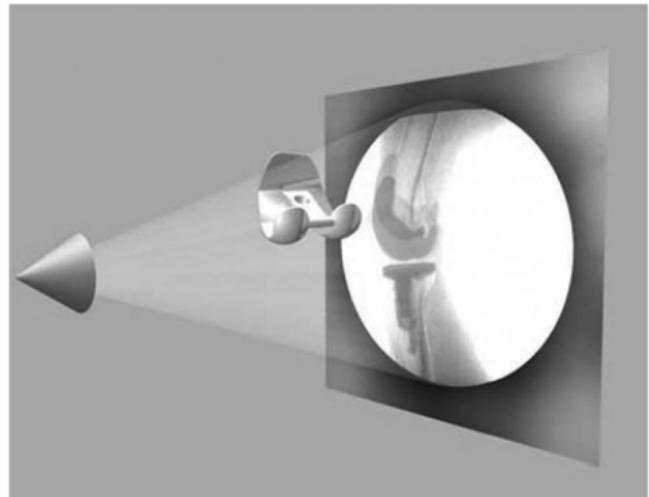
If we know the projective parameters of the fluoroscopy machine, can we tinker with $T_{implant}^{cam}$ so that our virtual projection matches the fluoroscopic image?



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]

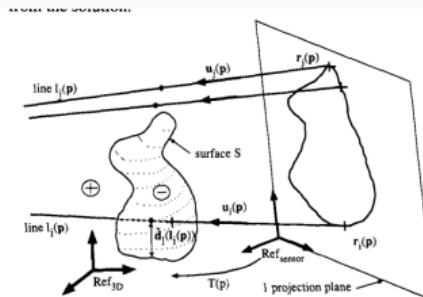
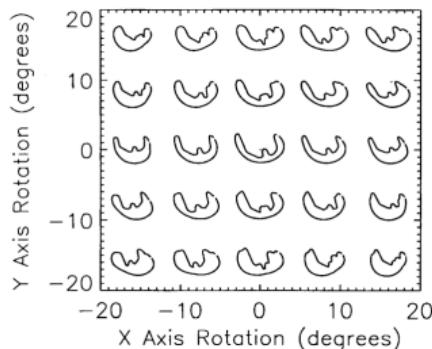


Fig. 2. Projection line to surface distance computation.



From [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

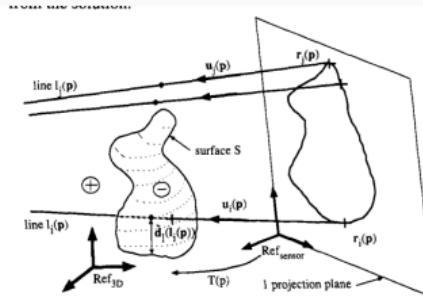
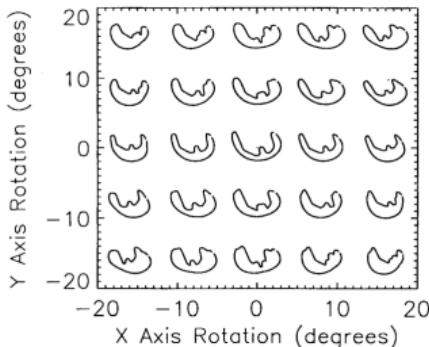


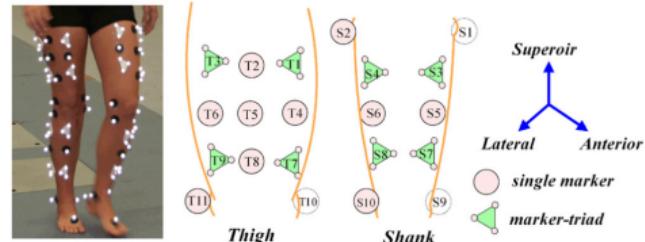
Fig. 2. Projection line to surface distance computation.



From [7]

Motion Capture (MoCap)

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



From [5]

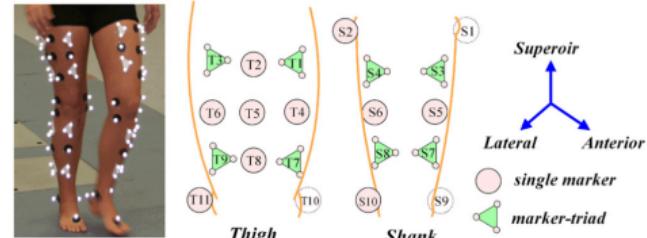
Limitations of Motion Capture

Skin Mounted

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

Bone Pins

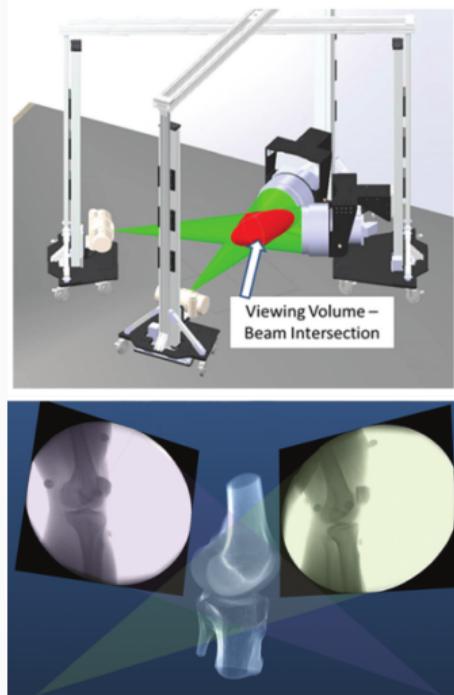
- Any volunteers?



From [5]

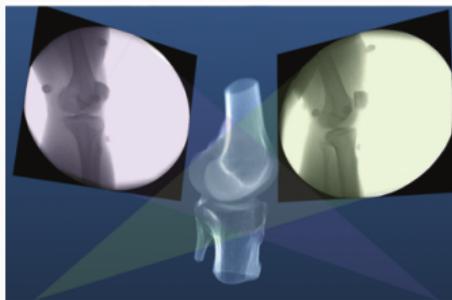
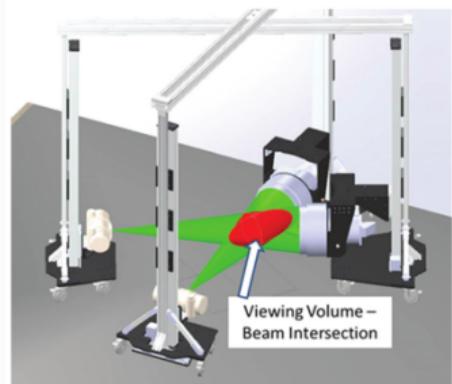
Biplane Imaging

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



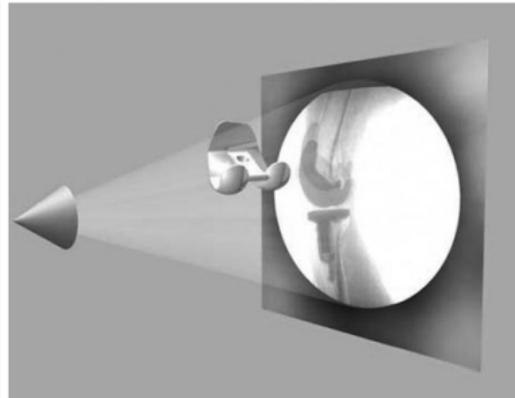
Limitations of Biplane Imaging

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



Iterative Projections

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



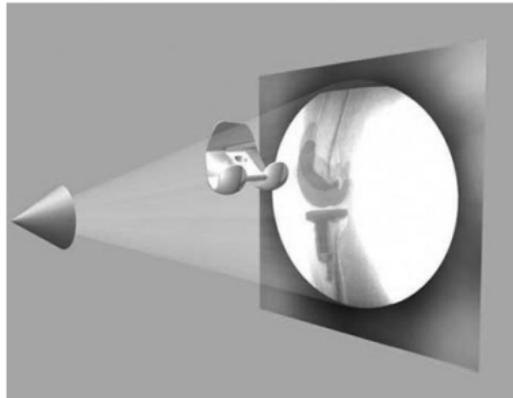
From [11]



From [24]

Limitations of (historic) Iterative Projection Methods

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



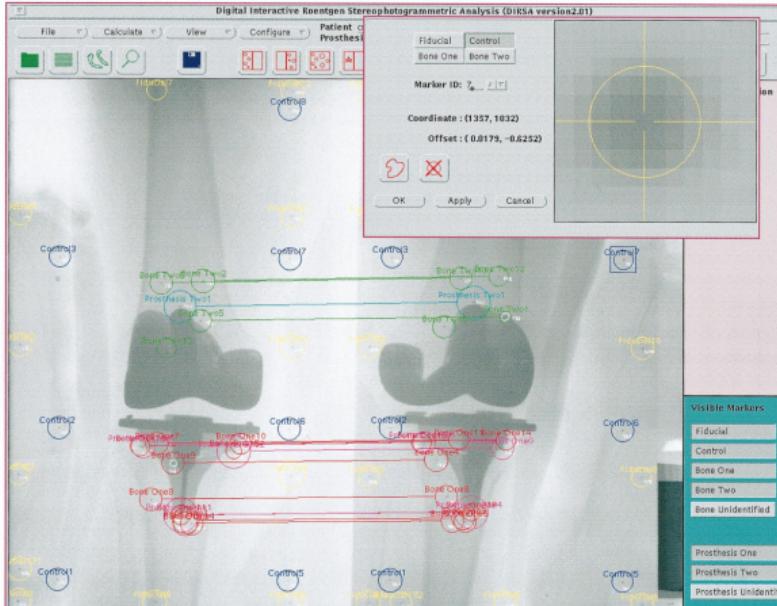
From [11]



From [24]

Roentgen Stereophotogrammetry (RSA)

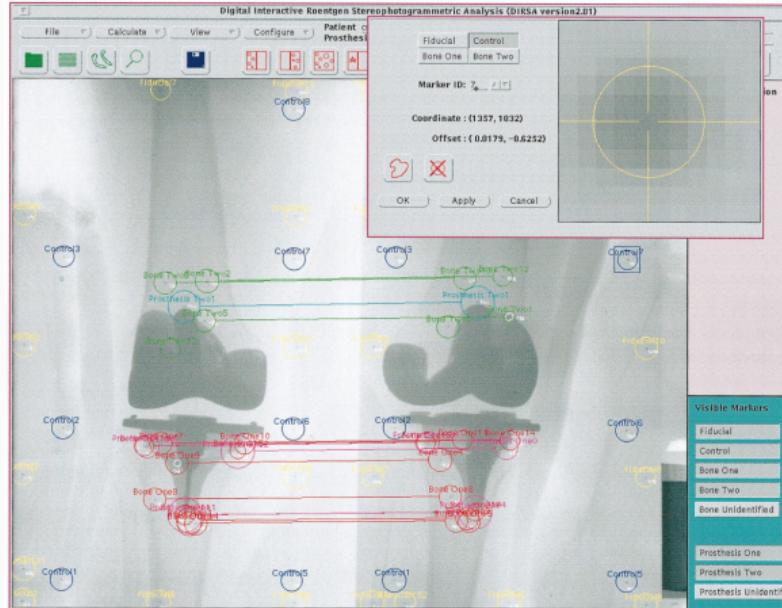
- Uses implanted tantalum beads for motion tracking [10, 4]
- Extremely accurate [12, 13]
- Gold standard Measurement [33]



From [10]

Limitations of RSA

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



From [10]

Aims

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

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Aim 5 - Joint Track Auto Toolkit

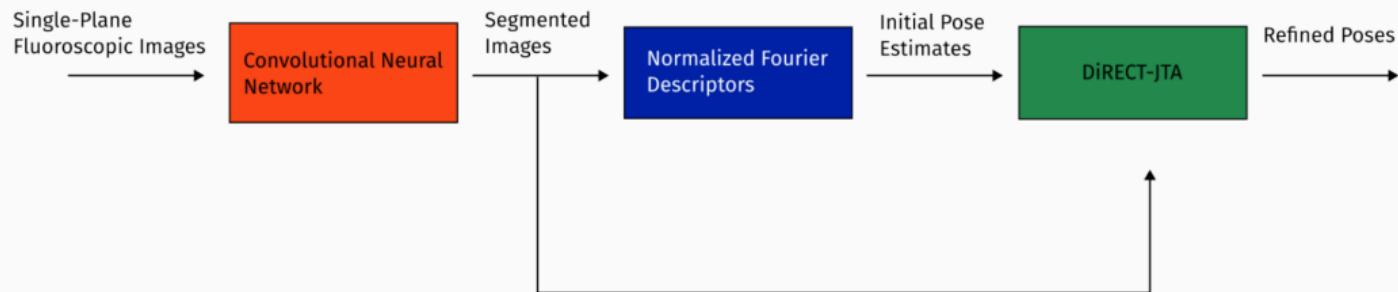
References

Goal

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

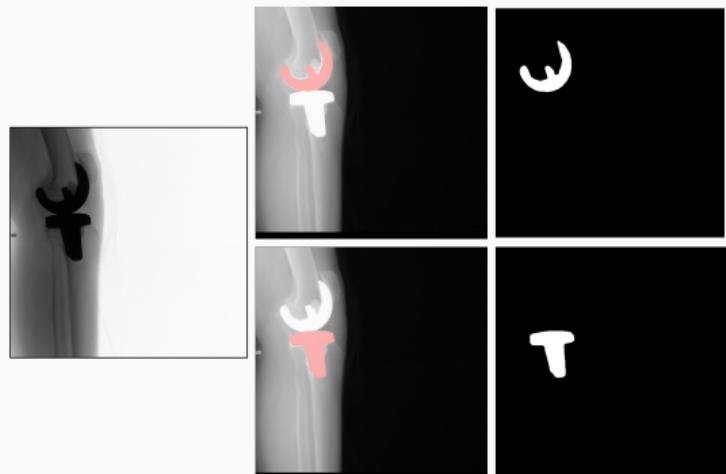
Method

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



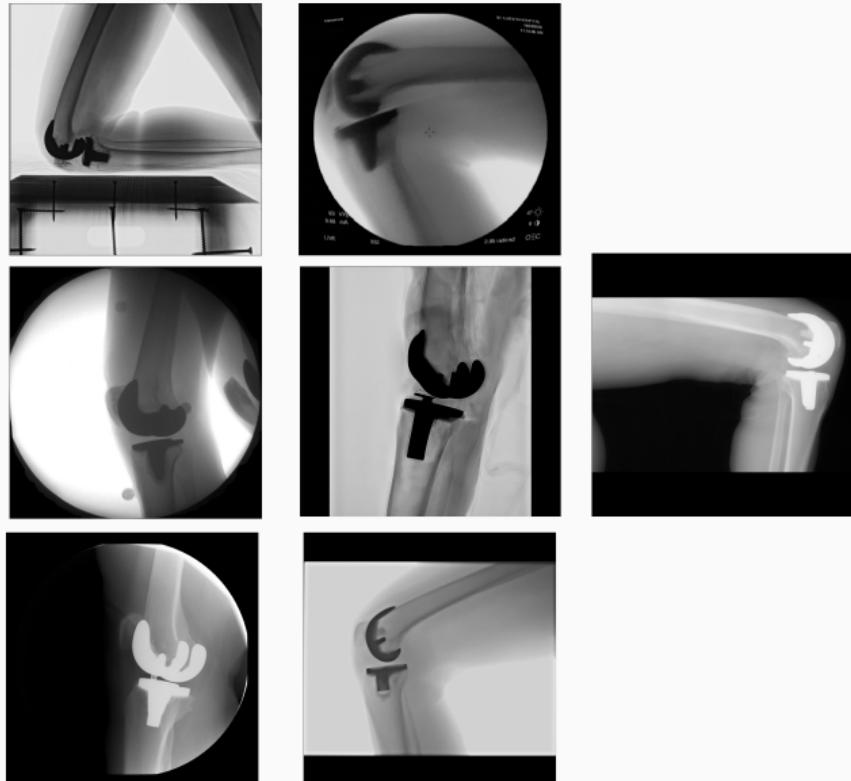
Autonomous Implant Detection Using Convolutional Neural Networks

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



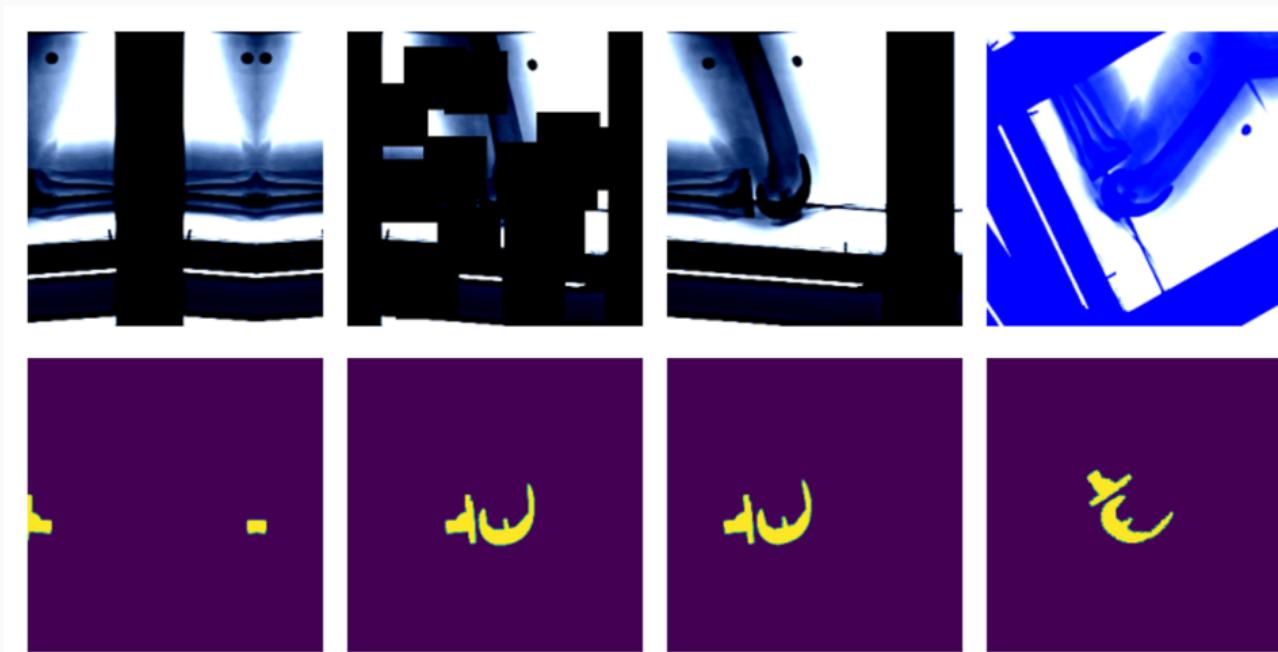
Neural Network Data

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



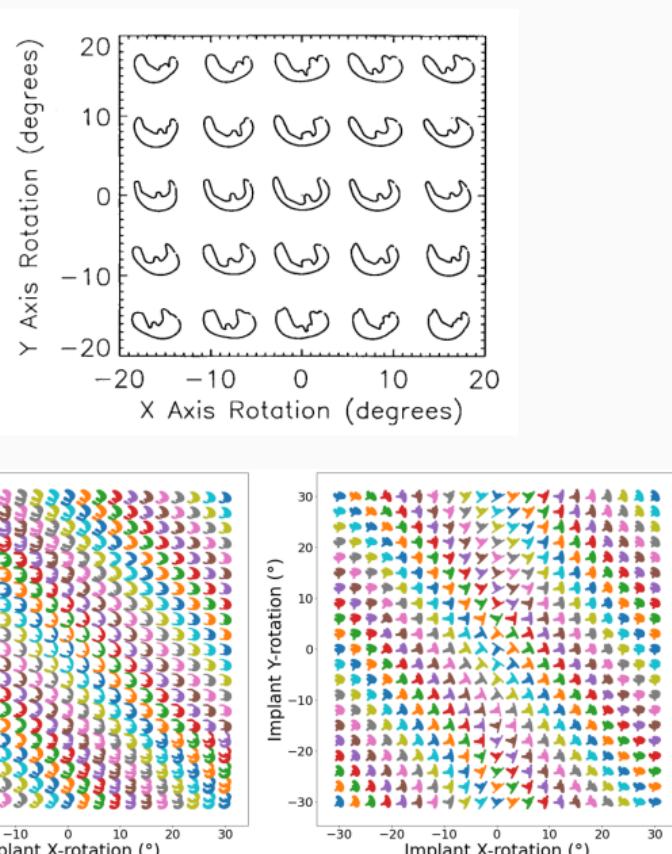
Neural Network Robustness

- Additional augmentations introduced during training [25].



Normalized Fourier Descriptor Shape Libraries

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



Pose Refinement Using Global Optimization

- Two main features
 - Objective function
 - Optimization routine

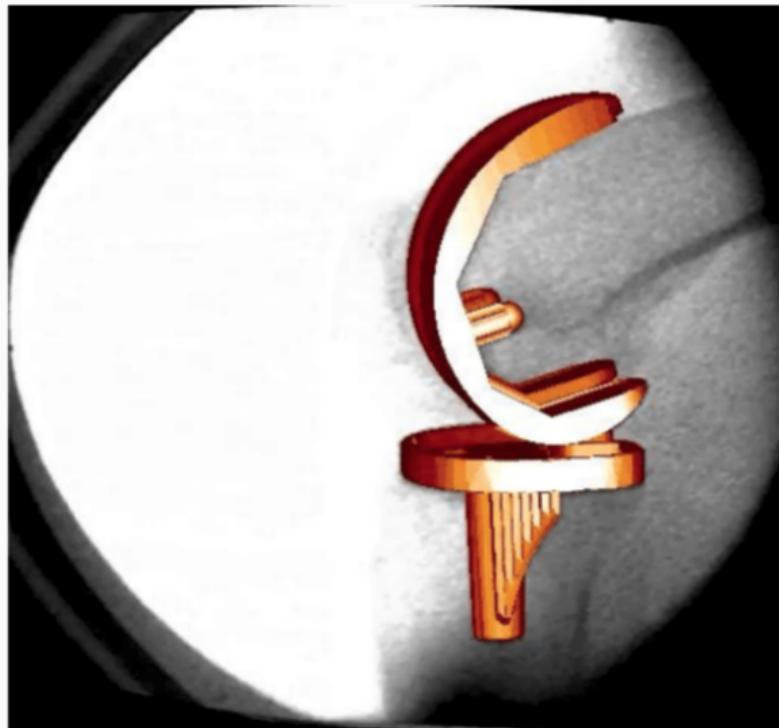
$$\underset{x}{\operatorname{argmin}} \{f(x) : x \in \Omega\}$$

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.

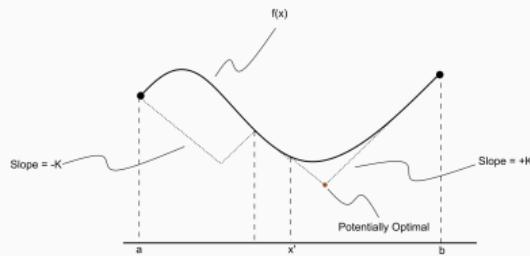
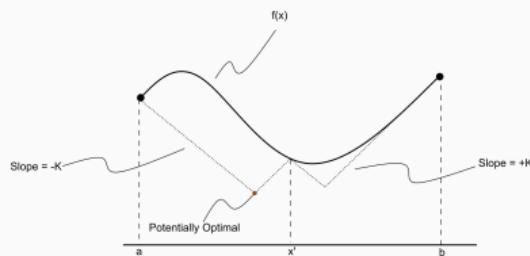
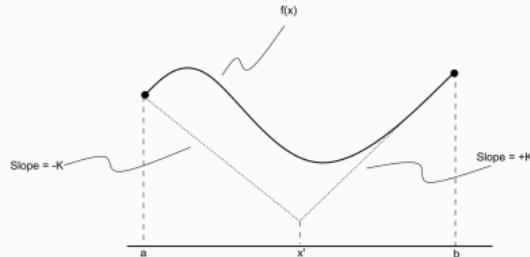


Optimization Routine

- 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?

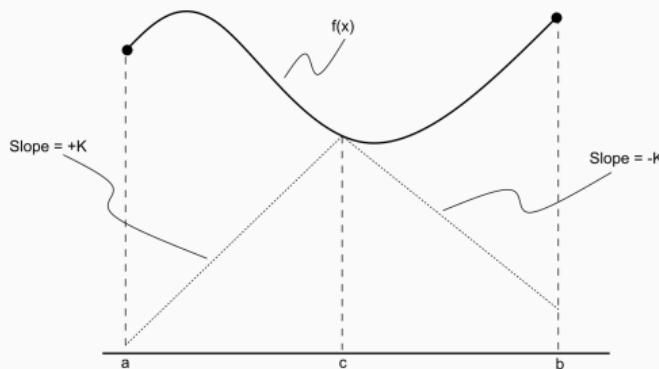


Lipschitzian Optimization without the Lipschitz Constant

Lipschitzian Optimization Without the Lipschitz Constant

D. R. JONES,¹ C. D. PERTTUNEN,² AND B. E. STUCKMAN³

- 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

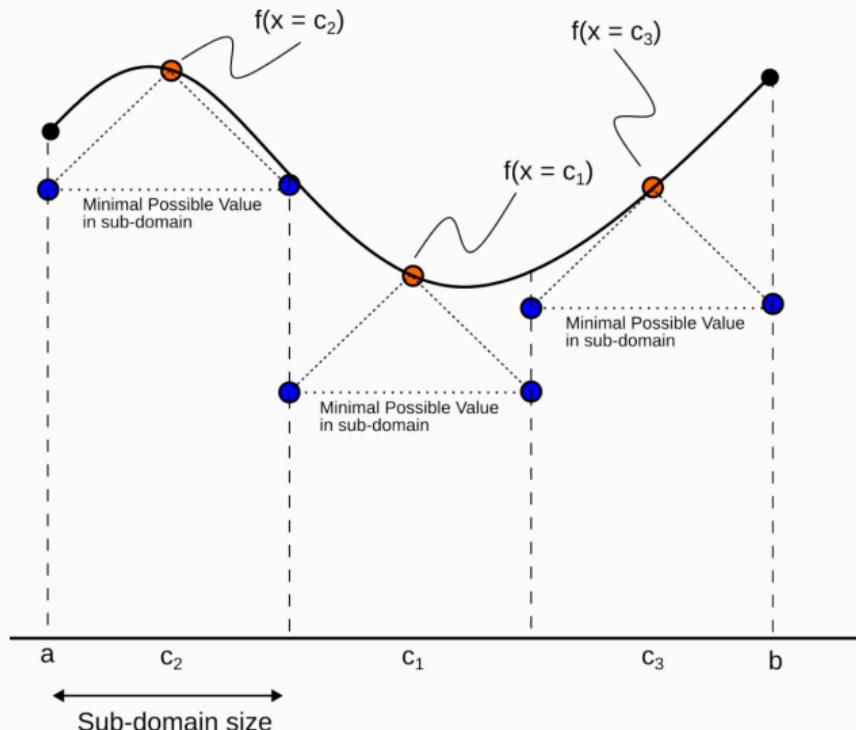
$$\begin{bmatrix} f(x = c_1) & d(c_1) \\ f(x = c_2) & d(c_2) \\ \vdots & \vdots \\ f(x = c_N) & d(c_N) \end{bmatrix}$$

Where

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

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

for $i \in [1, N]$



Another Iteration

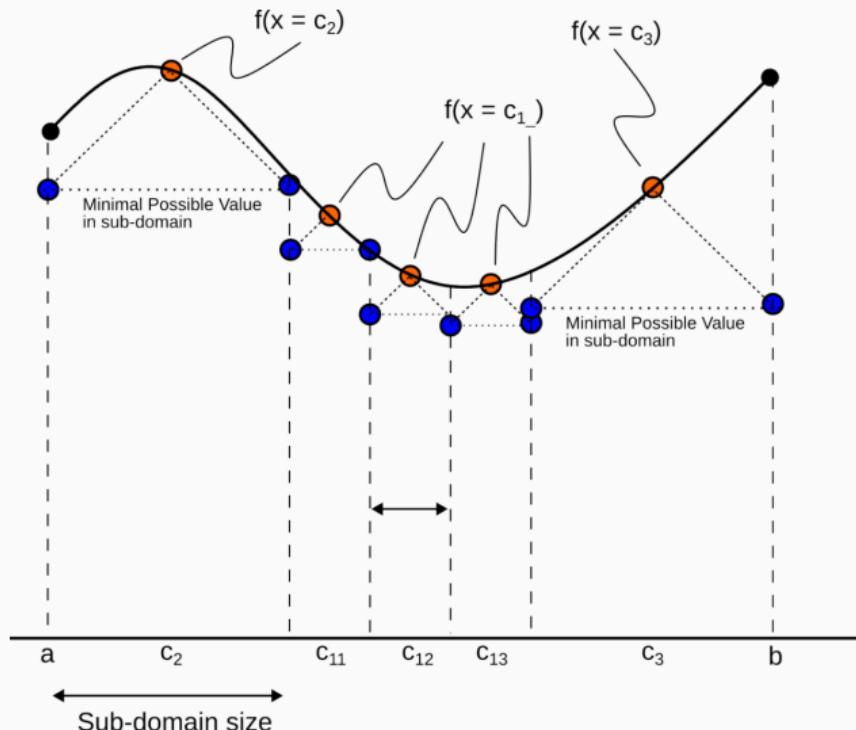
$$\begin{bmatrix} f(x = c_1) & d(c_1) \\ f(x = c_2) & d(c_2) \\ \vdots & \vdots \\ f(x = c_N) & d(c_N) \end{bmatrix}$$

Where

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

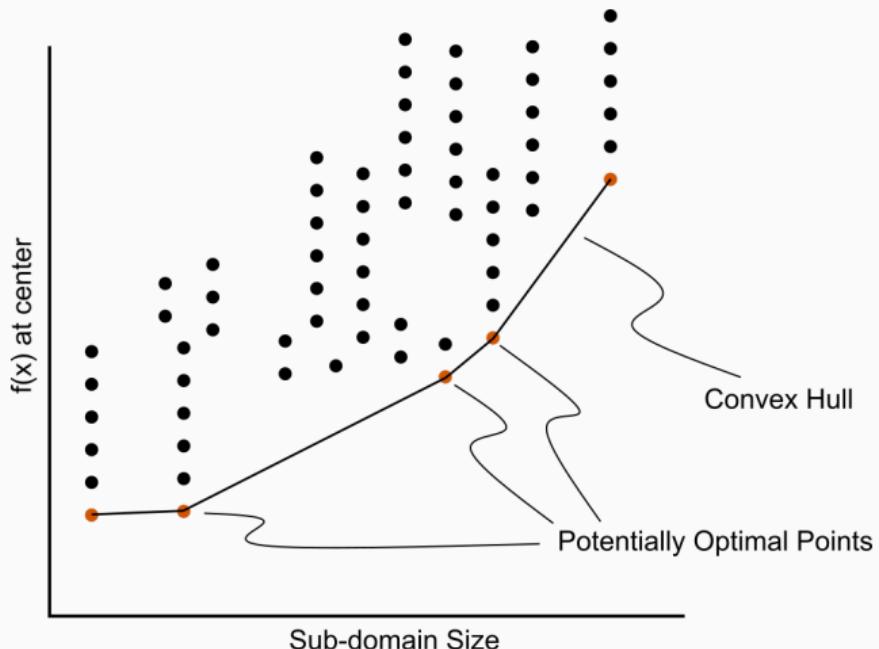
$d(c_i) \equiv$ Sub-domain size

for $i \in [1, N]$



Determining Potentially Optimal Regions

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



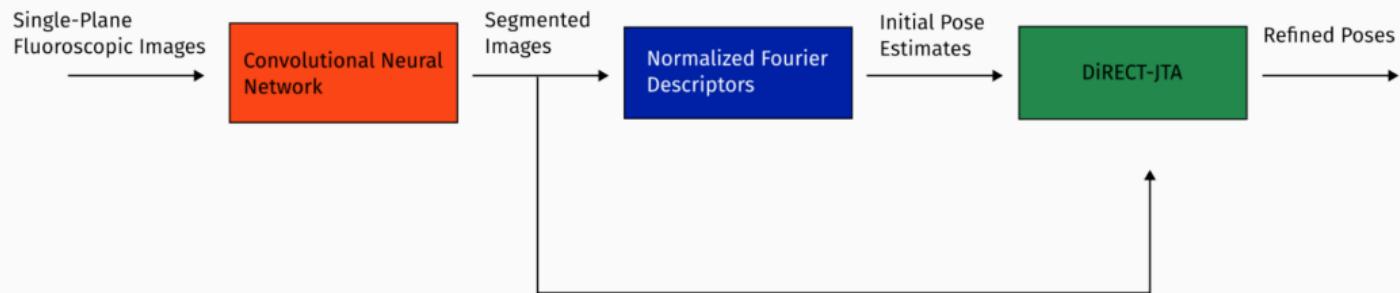
DiRECT for Joint Track Machine Learning

- 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

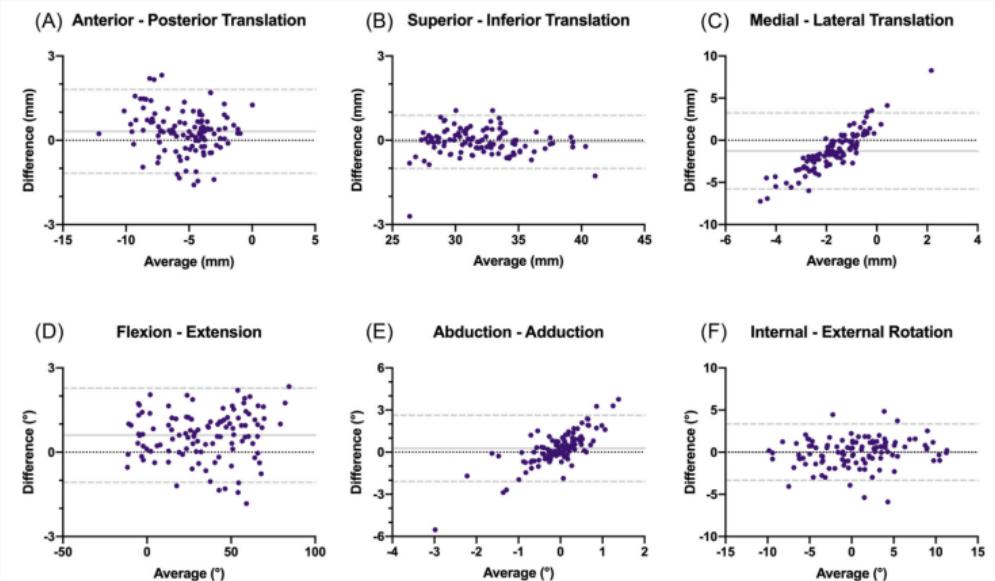
Testing Performance

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.

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

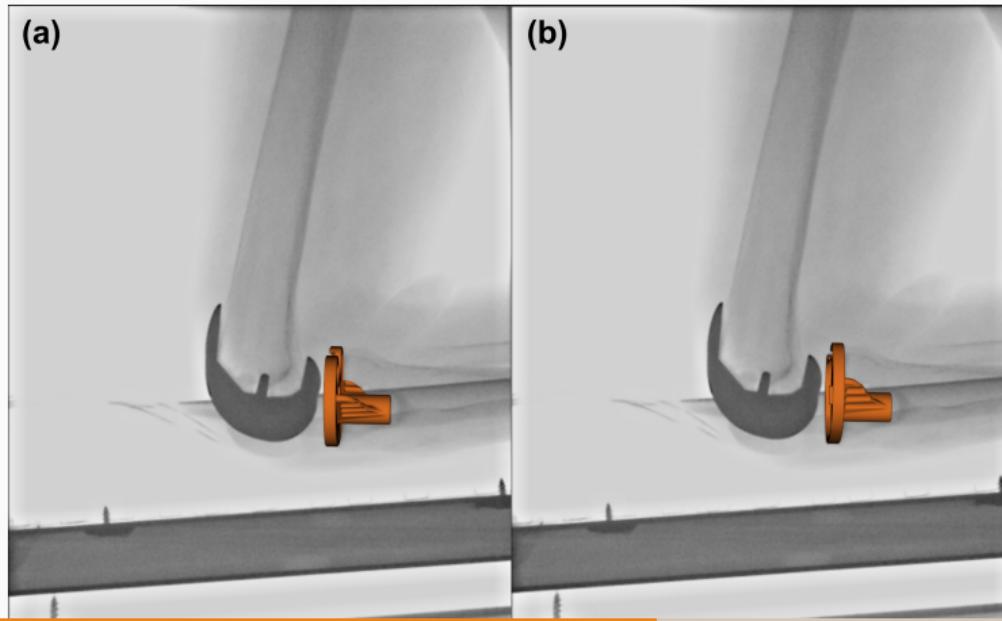
Where

$ML \equiv$ 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.

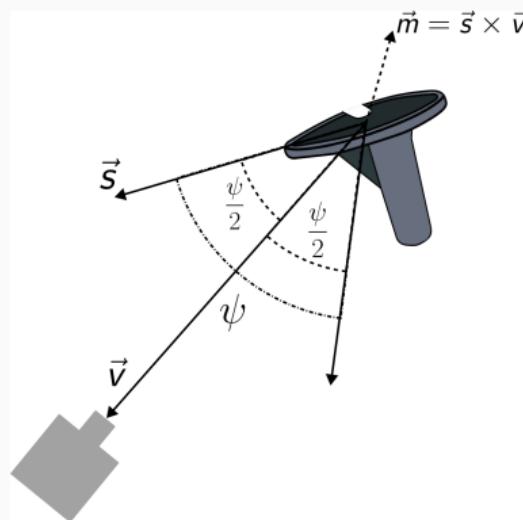
Found “ambiguous zone” within 3° of pure lateral pose with high propensity for symmetry traps [32].



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

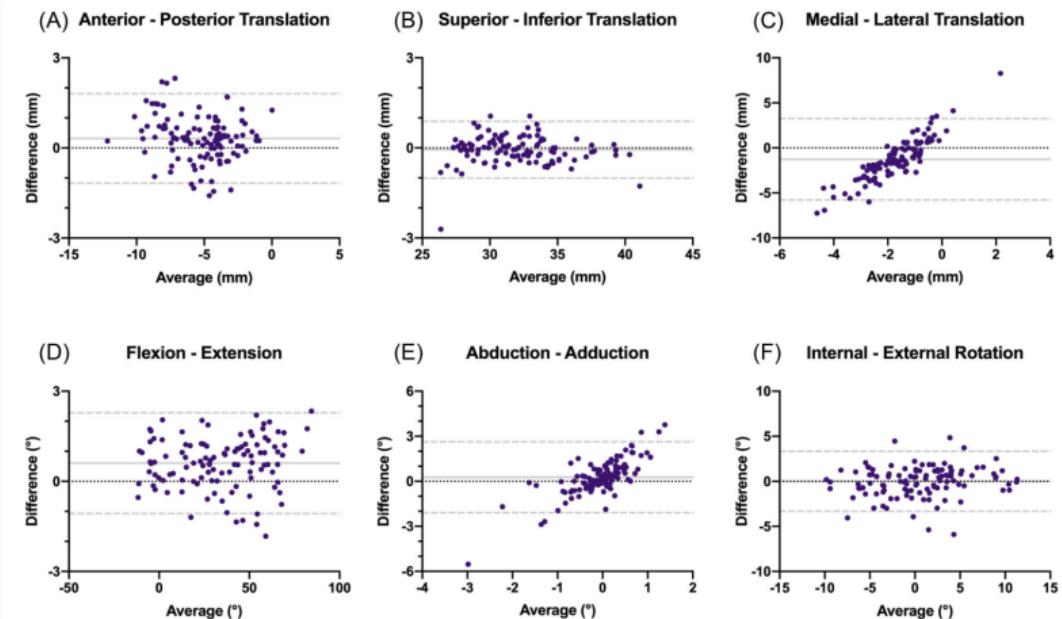
Binary Selection

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).

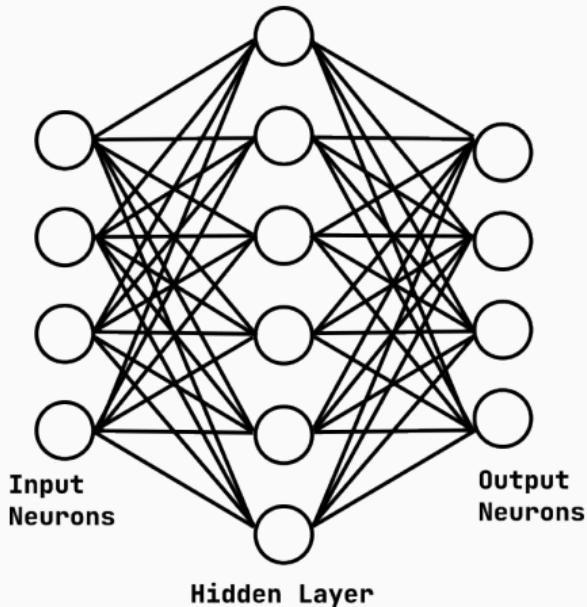
Bland-Altman Calibration Constant

- 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

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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

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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

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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

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

Presentations ii

- [4] Andrew Jensen et al. *Comparison of Clinical and Computational Implant Fit Analysis in Partial Knee Arthroplasty*. Podium. Phoenix, AZ, Feb. 2020.
- [5] Andrew Jensen et al. *Towards Routine Clinical Examination of 3D Joint Kinematics*. Korea, 2020.
- [6] Yifei Dai et al. *Comparative Analysis of Fixation Structure Design on the Primary Stability of Cementless TKA during Walking*. Podium. Online, Feb. 2021.
- [7] Yifei Dai et al. *Impact of Fixation Components on Primary Stability of Cementless TKA during Walking*. Podium. Online, Feb. 2021.
- [8] Andrew Jensen et al. *Accuracy of an Autonomous Method for Extracting Joint Kinematics from Single-Plane Fluoroscopy*. Oslo, Norway, 2021.

- [9] Andrew James Jensen et al. *An Autonomous Method for Extracting 3D Knee Replacement Kinematics from Dynamic Single Plane Fluoroscopic Images.* Online, 2021.
- [10] Jacob Griffith et al. *Automated Segmentation and Grading of Rodent Knee OA Histology Using Convolutional Neural Networks.* Poster. Tampa, FL, Feb. 2022.
- [11] Andrew Jensen, Lindsey Palm, and Scott Banks. *Autonomous Measurement of 3D TKA Kinematics from Dynamic Single-Plane Fluoroscopic Images.* Podium. Tampa, FL, Feb. 2022.
- [12] Andrew Jensen. *Deep Learning for Image Processing in Orthopaedics.* Virtual Scientific Session. Online, Jan. 2023.

Publications

- [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]. (Visited on 05/03/2022).

Publications ii

- [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). ISSN: 0736-0266, 1554-527X. DOI: 10.1002/jor.25518. (Visited on 02/13/2023).

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

References

- [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. (Visited on 02/20/2023).
- [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).
- [4] Göran Selvik. “**Roentgen Stereophotogrammetry: A Method for the Study of the Kinematics of the Skeletal System**”. In: *Acta Orthopaedica Scandinavica* 60.sup232 (Jan. 1989), pp. 1–51. ISSN: 0001-6470. DOI: 10.3109/17453678909154184. (Visited on 02/14/2023).

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- [5] Mario A. Lafortune et al. “**Three-Dimensional Kinematics of the Human Knee during Walking.**”. In: *Journal of Biomechanics* (1992). DOI: 10.1016/0021-9290(92)90254-x.
- [6] S. Lavallee and R. Szeliski. “**Recovering the Position and Orientation of Free-Form Objects from Image Contours Using 3D Distance Maps**”. In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* 17.4 (Apr. 1995), pp. 378–390. ISSN: 01628828. DOI: 10.1109/34.385980. (Visited on 05/12/2021).
- [7] S.A. Banks and W.A. Hodge. “**Accurate Measurement of Three-Dimensional Knee Replacement Kinematics Using Single-Plane Fluoroscopy**”. In: *IEEE Transactions on Biomedical Engineering* 43.6 (June 1996), pp. 638–649. ISSN: 00189294. DOI: 10.1109/10.495283. (Visited on 03/22/2021).
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