Joint Track Machine Learning

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Outline

Acknowledgments

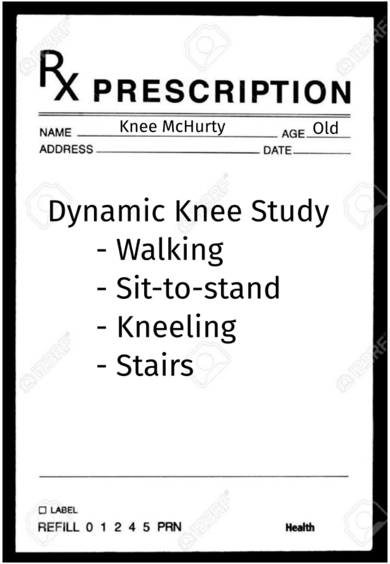
I would like to thank the McJunkin Family Charitable Foundation for their generous grant that supports this work.

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

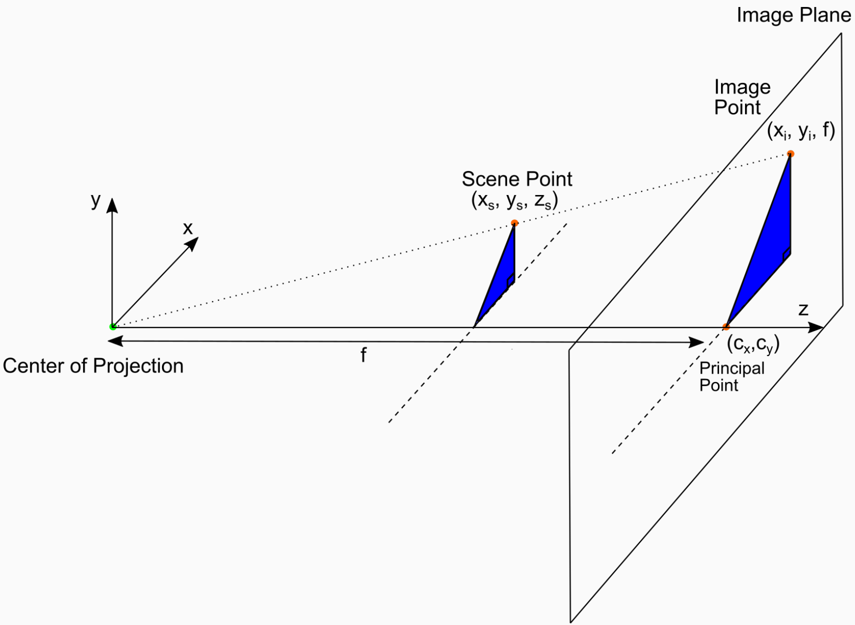
Orthopaedic surgeons and clinicians would readily adopt a practical and inexpensive technology that allows them to measure a patient's knee kinematics during activities of daily living.



Constraints

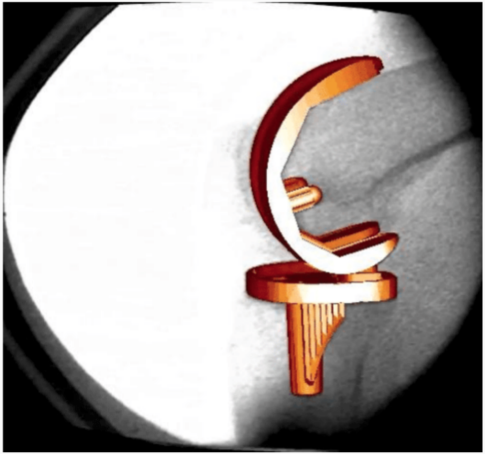
- It must fit within a standard clinical workflow
- The technology must utilize equipment commonly found in hospitals
- There must not be significant human supervision nor interaction to generate an examination report.

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

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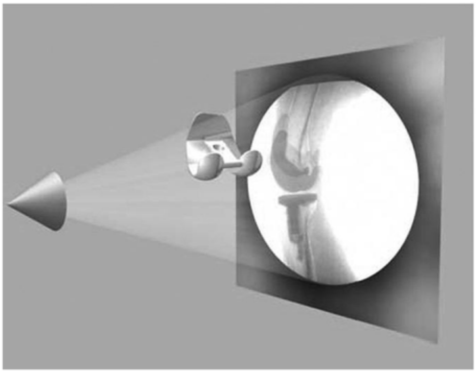


From [11]

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]

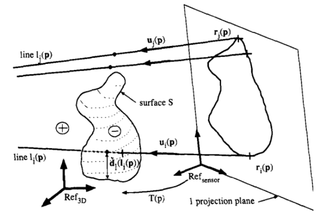
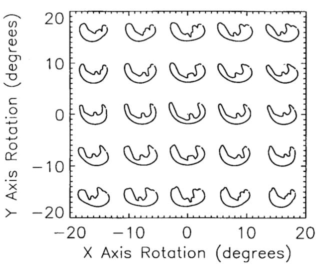


Fig. 2. Projection line to surface distance computation.

From [6]



Limitations of Pre-Computed Projections

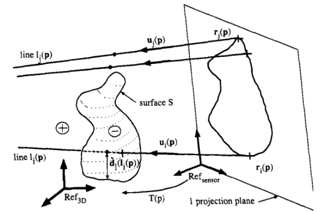
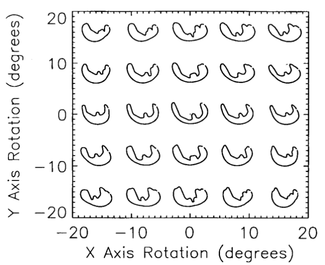


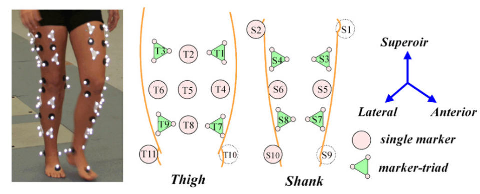
Fig. 2. Projection line to surface distance computation.

From [6]

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

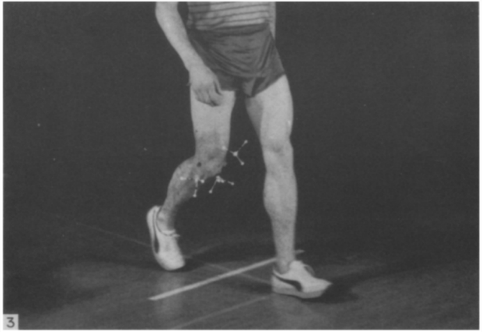


Motion Capture (MoCap)

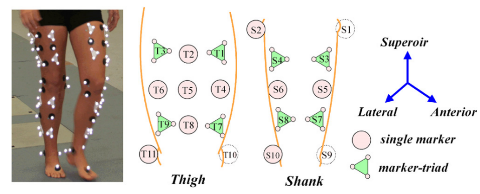


From [16]

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



Limitations of Motion Capture



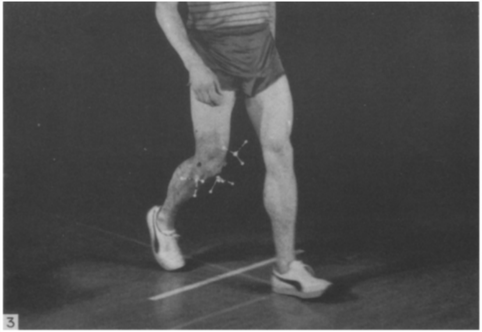
From [16]

Skin Mounted

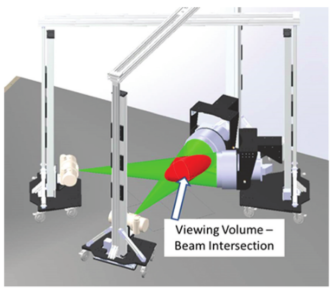
- Doesn't accurately describe underlying skeletal motion with clinical accuracy [16, 19, 21].

Bone Pins

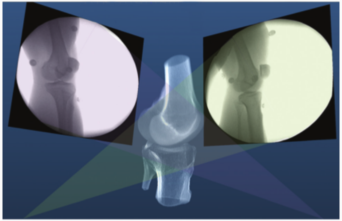
- Any volunteers?



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

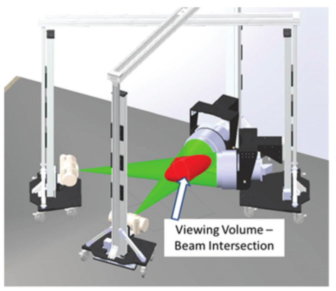


Both from [20]



Limitations of Biplane Imaging

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



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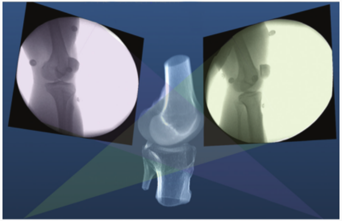
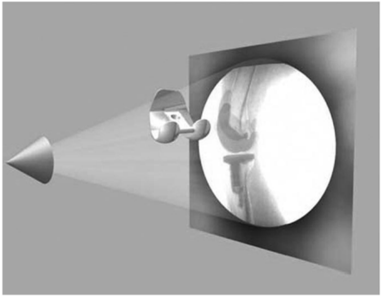


Iterative Projections

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

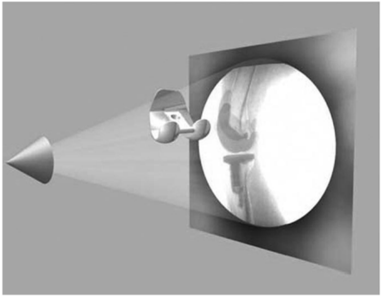


From [11]

From [24]

Limitations of (historic) Iterative Projection Methods

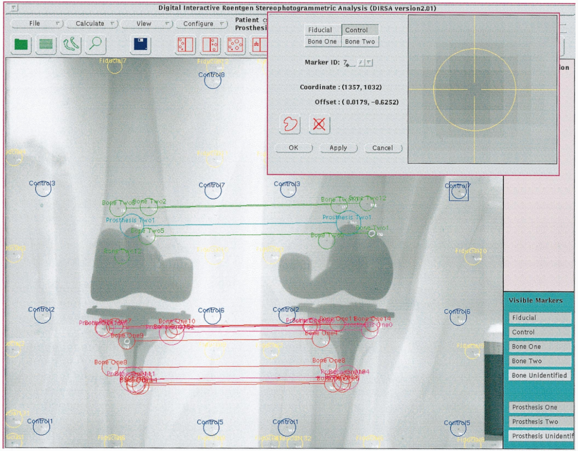
- Requires human supervision for:
  - Pose initialization
  - Escaping local minima
  - Implant detection
- Chaotic and Noisy objective function



From [11]

From [24]

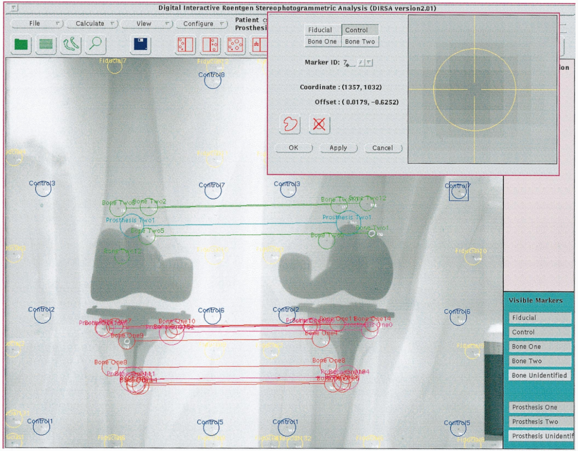
- Uses implanted tantalum beads for motion tracking [10, 4]
- Extremely accurate [12, 13]
- Gold standard Measurement [33]



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

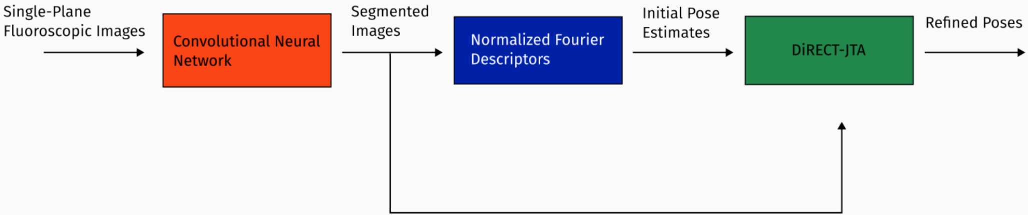
Aim 5
Joint Track Auto Toolkit

Goal

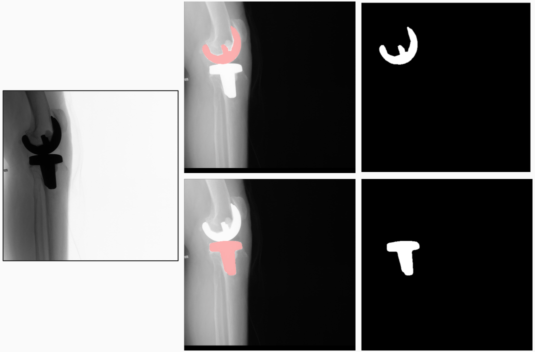
Demonstrate the feasibility of a fully autonomous, model-image registration pipeline.

Method

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



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



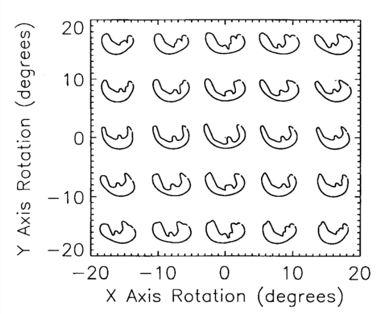
Neural Network Data

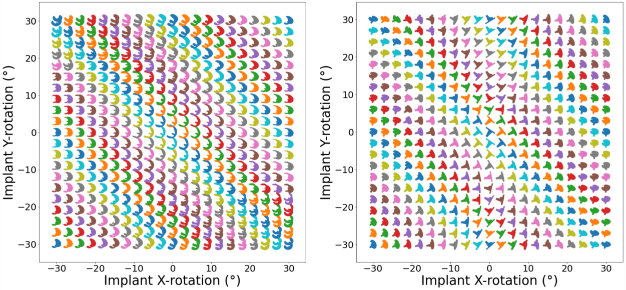
- ~8000 images
  - 7 TKA kinematics studies
    - 71 subjects
    - 7 implant manufacturers
    - 36 distinct implants
    - Squat, lunge, kneel, stair ascent

- 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

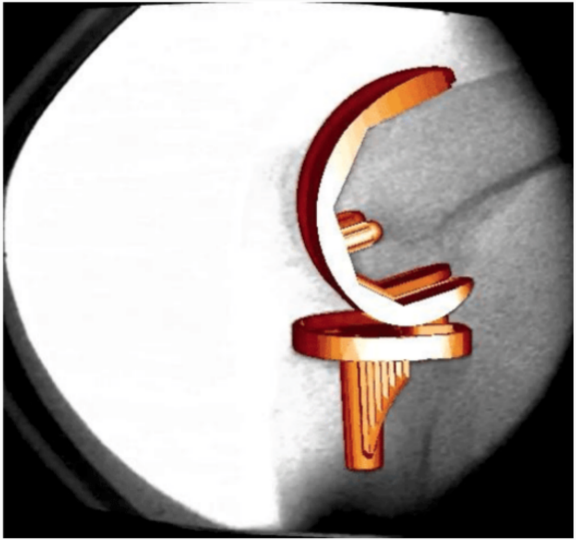
$$\underset{x}{\operatorname{argmin}}\{f(x) : x \in \Omega\}$$

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

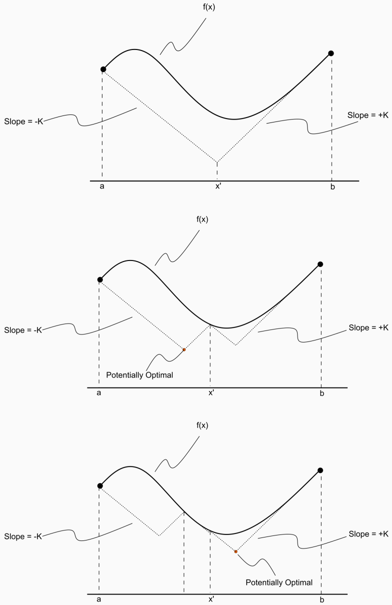
- Dilation decreases sensitivity to perturbations.
- Multi-stage optimization can reduce dilation back to original edges.

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?

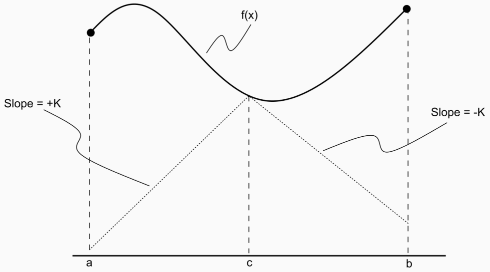


Lipschitzian Optimization without the Lipschitz Constant

Lipschitzian Optimization
Without the Lipschitz Constant

D. R. Jones,[1] C. D. Perttunen,[2] and B. E. Stuckman[3]

- 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

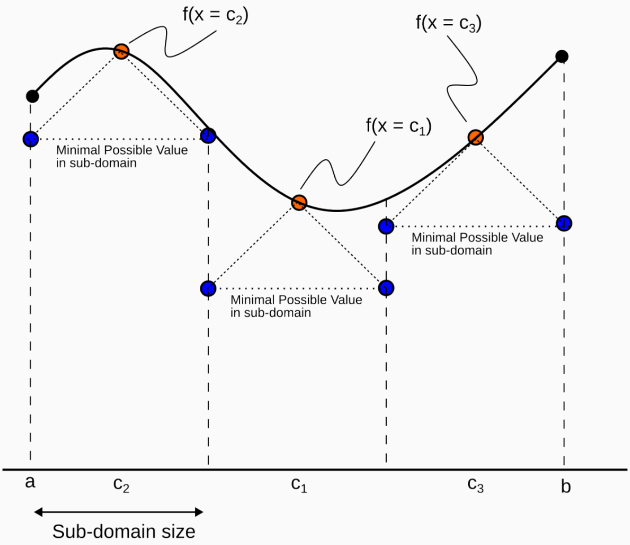


Trisecting Region

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

Where

$$f(x = c_i) \equiv \text{Sampled function value}$$
$$d(c_i) \equiv \text{ Sub-domain size}$$
$$\text{for } i \in [1, N]$$



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

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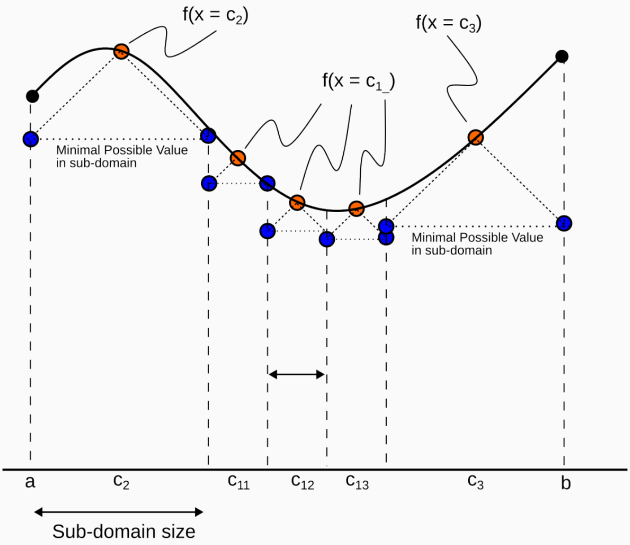
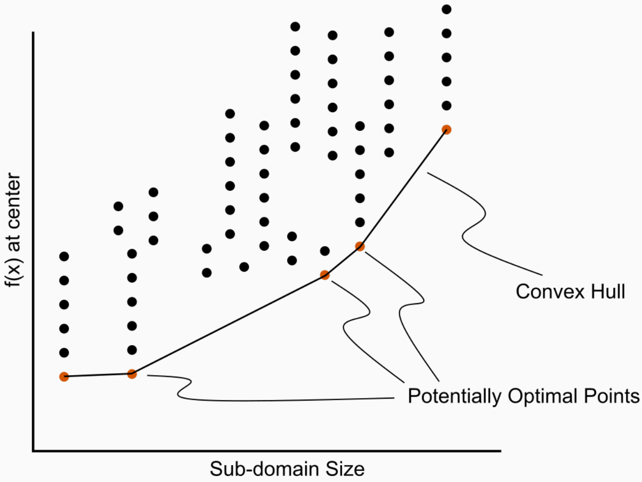
$$\text{for } i \in [1, N]$$



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



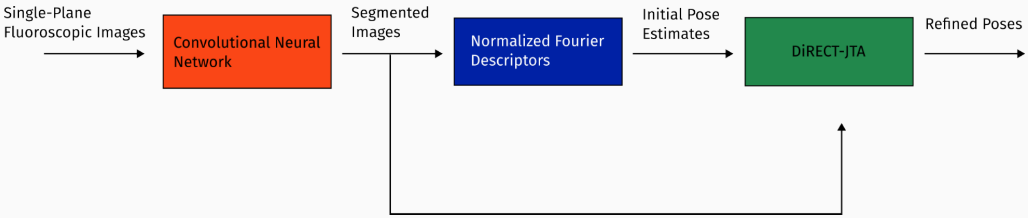
DiRECT for Joint Track Machine Learning

- 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 (*else*)	1

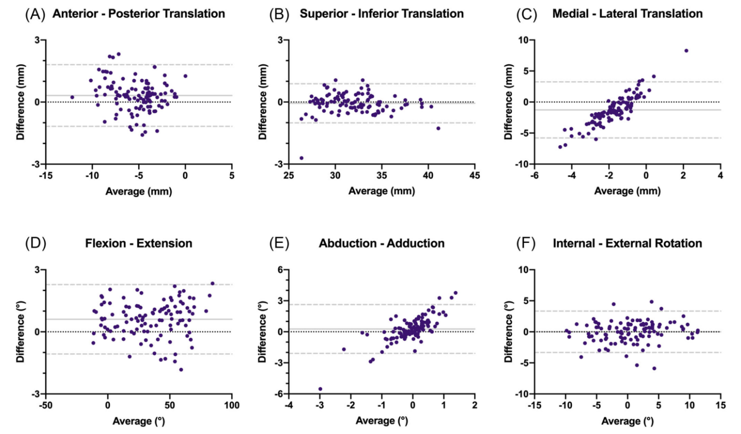
Testing Performance

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



Validation

- Independent research group using Model-Based RSA.
- Determine the level of concordance between the two measurement systems
    - Bland-Altmann 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

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.

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

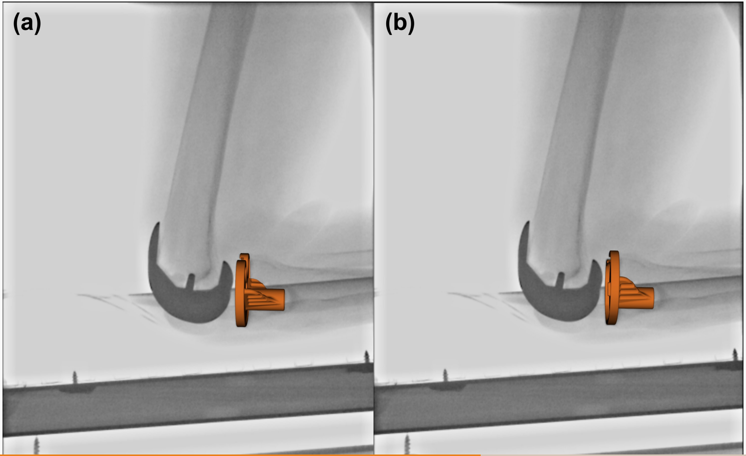
Where

$$ML \equiv \text{ Relative mediolateral translation}$$

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.

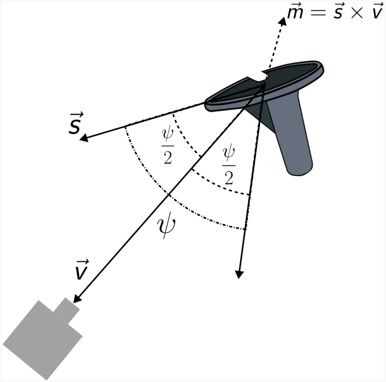
Found "ambiguous zone" within 3° of pure lateral pose with high propensity for symmetry traps [32].



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, $\cos(\theta) = \dfrac{\vec{v} \cdot \vec{s}}{||\vec{v}||||\vec{s}||}$
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-Altmann Calibration Constant
- Fully Connected Network

Virtual Ligaments

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

Where

$$VV \equiv \text{ Relative Varus-Valgus rotation}$$

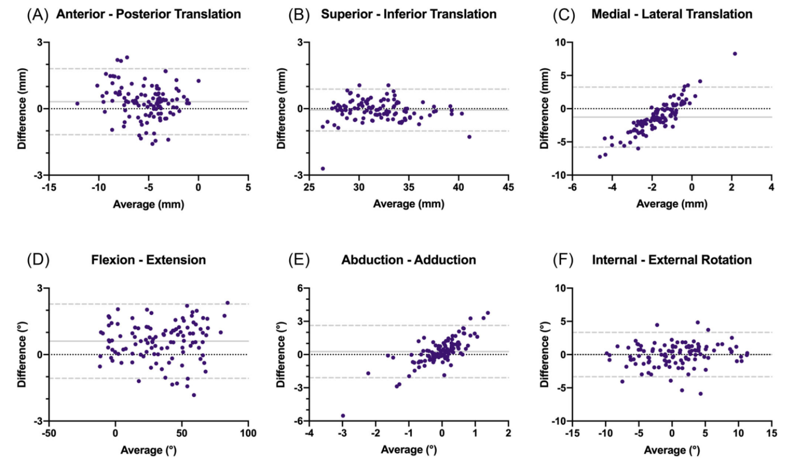
Binary Selection

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).

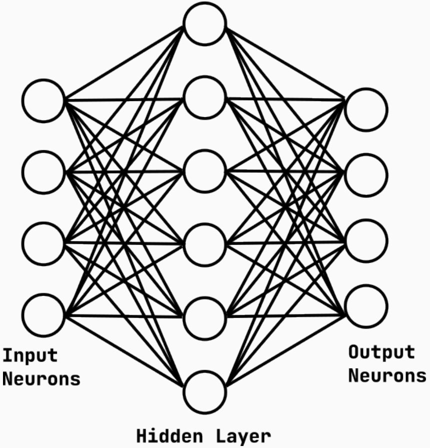
Bland-Altmann Calibration Constant

- 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-Altmann Calibration
    - Fully Connected Network

Journal paper will be ready for submission by June.

Aims

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.

Goal

Establish a “standard kinematics exam” by determining the most statistically and anatomically relevent 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)

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 Luscus - 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.

[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.compbiomed.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).

[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 Algorith 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).

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