Joint Track Machine Learning

Andrew Jensen

March 9, 2023

Outline

Acknowledgments

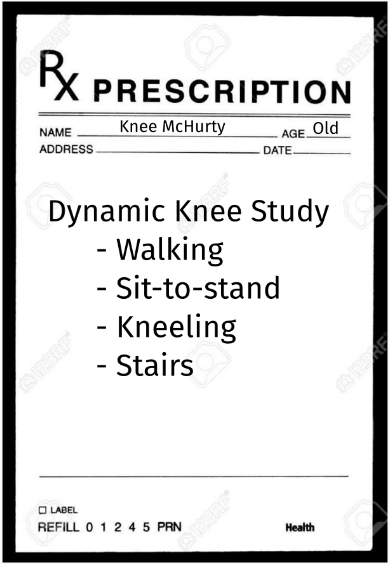
I would like to thank the McJunkin Family Charitable Foundation for their generous grant that supports this work.

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

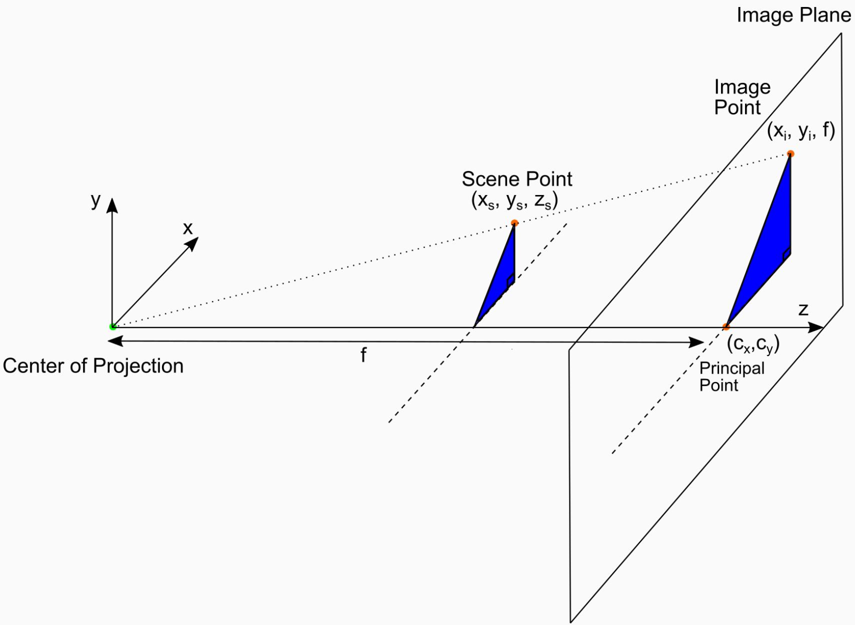
Orthopaedic surgeons and clinicians would readily adopt a practical and inexpensive technology that allows them to measure a patient's knee kinematics during activities of daily living.



Constraints

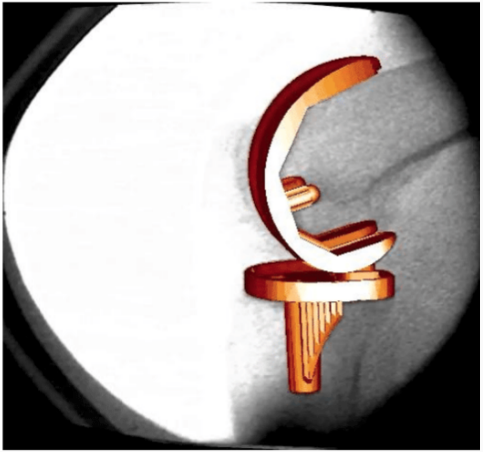
- It must fit within a standard clinical workflow
- The technology must utilize equipment commonly found in hospitals
- There must not be significant human supervision nor interaction to generate an examination report.

Background - Projective Geometry



Background - Model-Image Registration

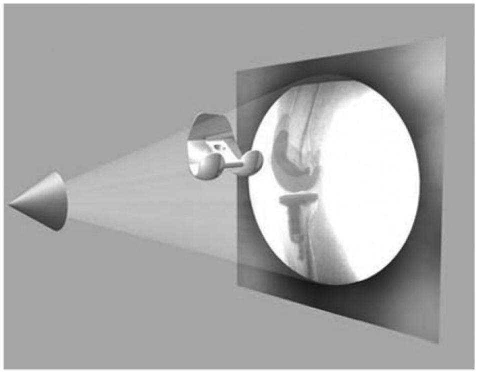
If we know the projective parameters of the fluoroscopy machine, can we tinker with $T_{implant}^{cam}$ so that our virtual projection matches the fluoroscopic image?



From [11]

Background - Model-Image Registration

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]

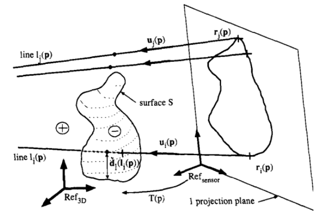
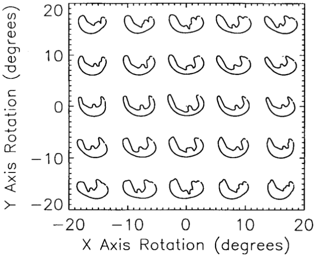


Fig. 2. Projection line to surface distance computation.

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
    - Inaccuaracy with naive edge detection

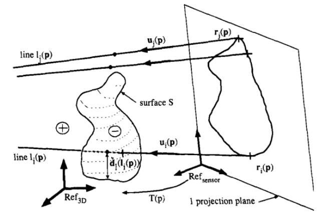
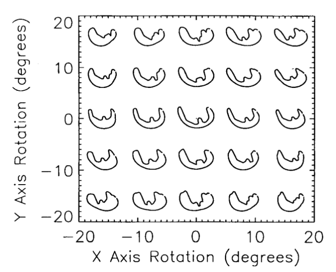


Fig. 2. Projection line to surface distance computation.

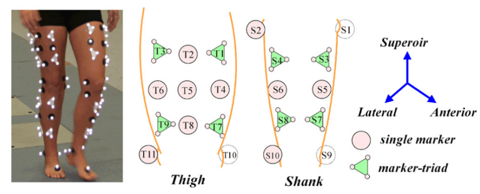
From [6]



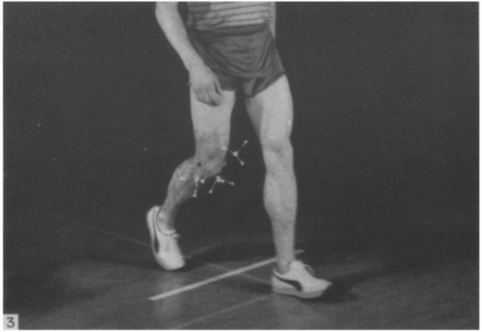
From [7]

Motion Capture (MoCap)

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

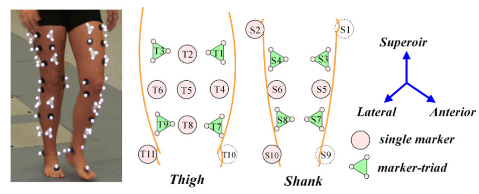


From [16]



From [5]

Limitations of Motion Capture



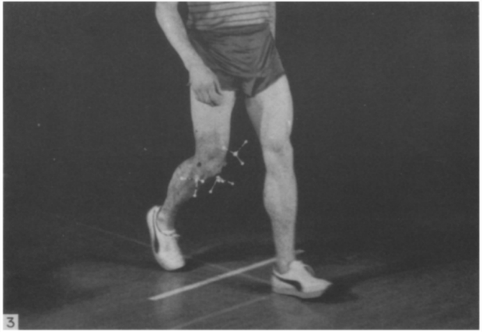
From [16]

Skin Mounted

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

Bone Pins

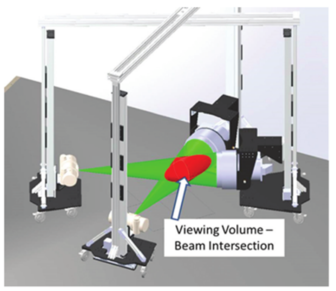
- Any volunteers?



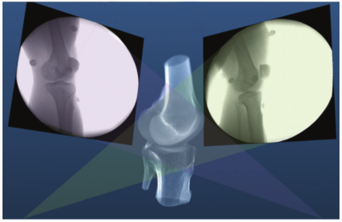
From [5]

Biplane Imaging

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

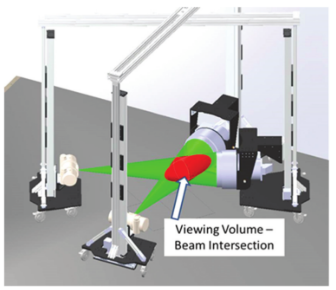


Both from [20]

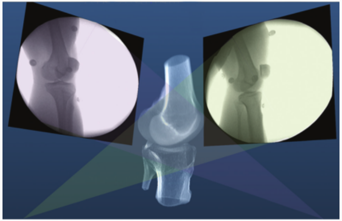


Limitations of Biplane Imaging

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

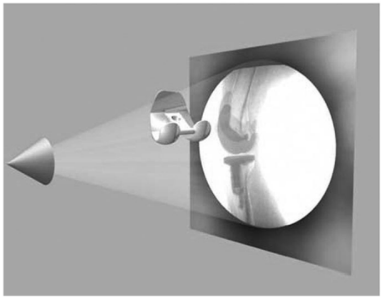


Both from [20]



Iterative Projections

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

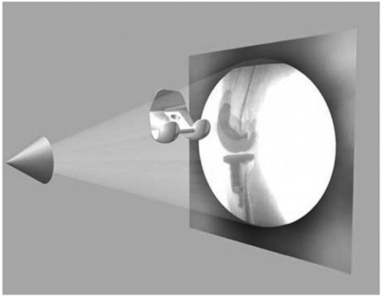


From [11]

From [24]

Limitations of (historic) Iterative Projection Methods

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

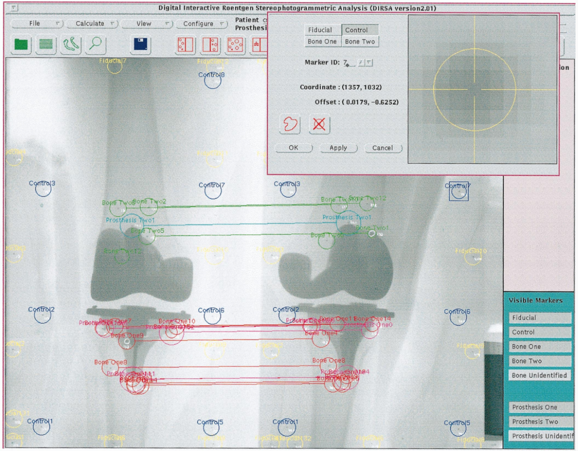


From [11]

From [24]

Roentgen Stereophotogrammetry (RSA)

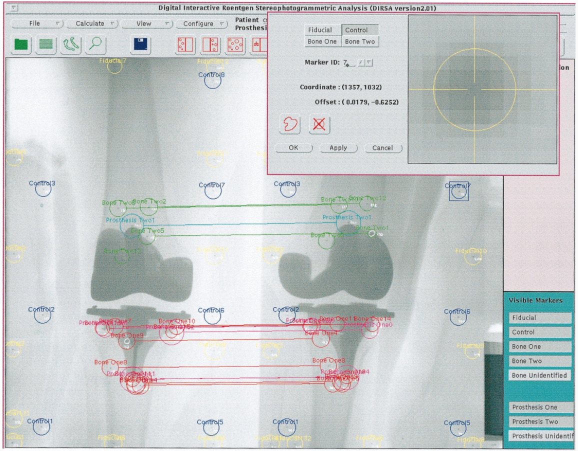
- Uses implanted tantalum beads for motion tracking [10, 4]
- Extremely accurate [12, 13]
- Gold standard Measurement [33]



From [10]

Limitations of RSA

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



From [10]

Aims

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

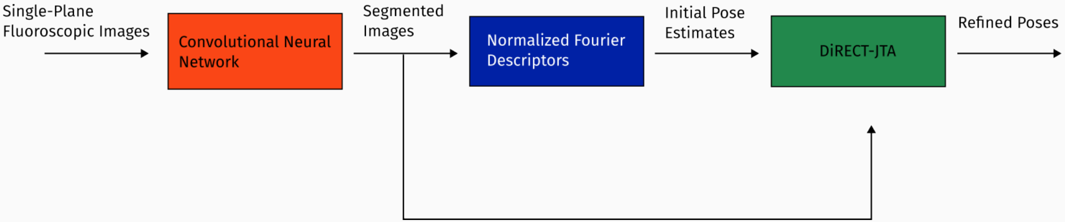
References

Goal

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

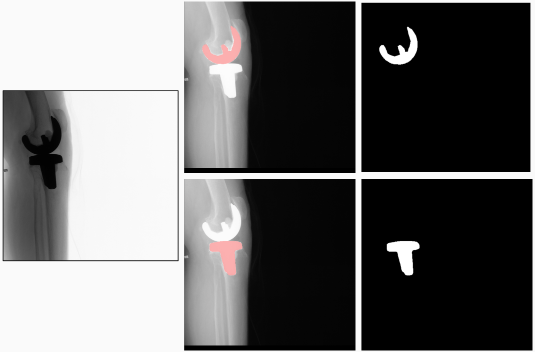
Method

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



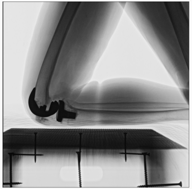
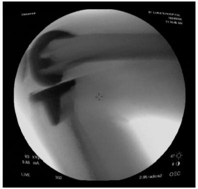
Autonomous Implant Detection Using Convolutional Neural Networks

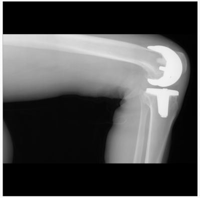
- 2 CNNs
    - Femoral and Tibial implants
- High Resolution Network [27]



Neural Network Data

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

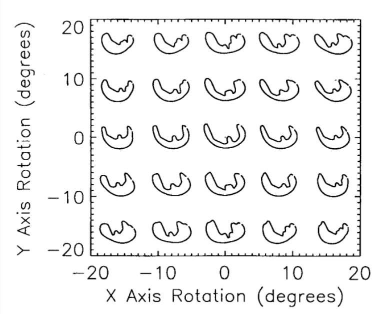



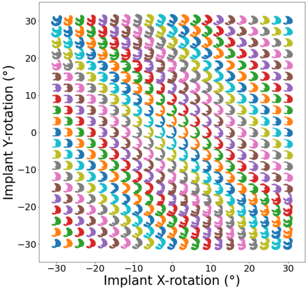
Neural Network Robustness

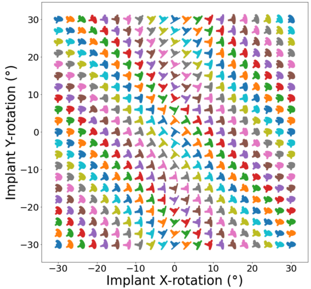
- Additional augmentations introduced during training [25].

Normalized Fourier Descriptor Shape Libraries



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





Pose Refinement Using Global Optimization

- Two main features
  - Objective function
  - Optimization routine

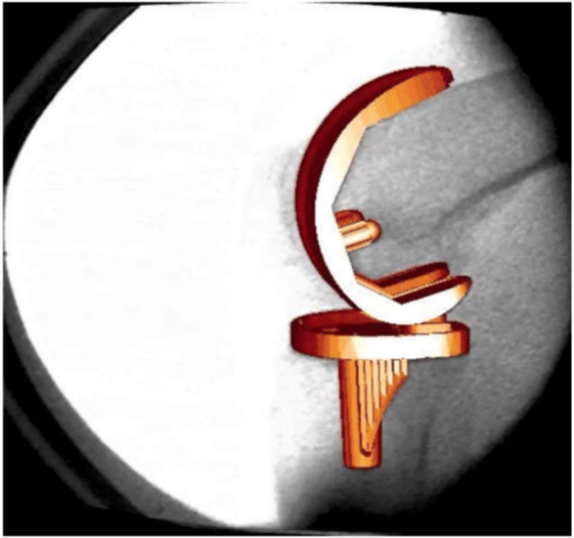
$$\underset{x}{\operatorname{argmin}}\{f(x) : x \in \Omega\}$$

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

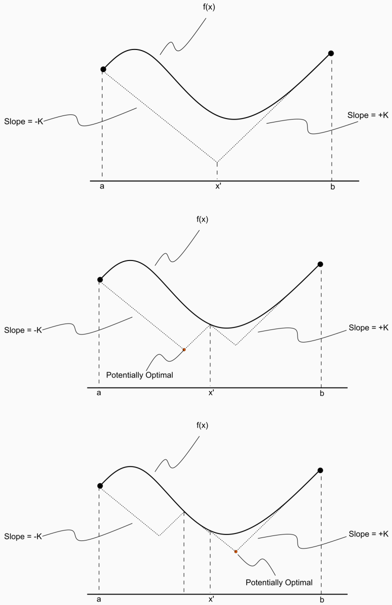
- Dilation decreases sensitivity to perturbations.
- Multi-stage optimization can reduce dilation back to original edges.

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?

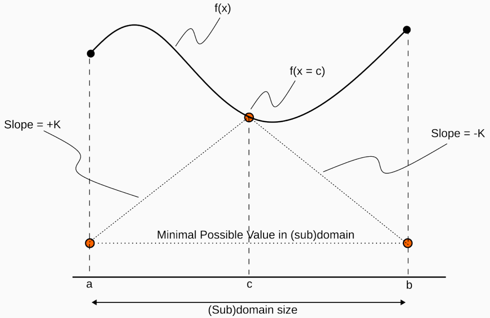


Lipschitzian Optimization without the Lipschitz Constant

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

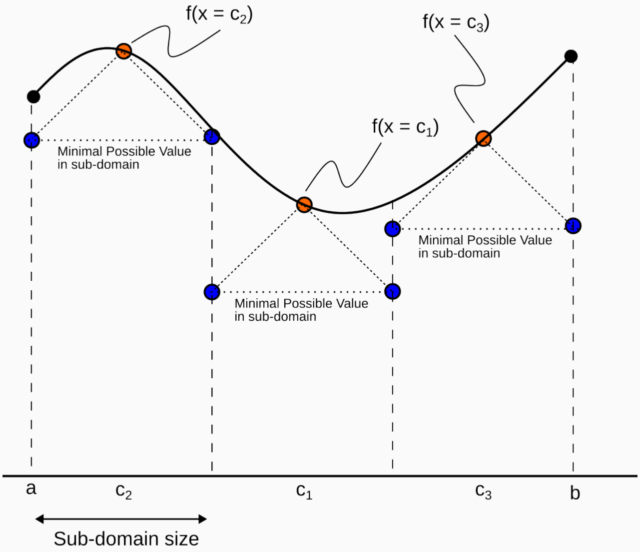
$$\begin{bmatrix} f(x = c_1) & d(c_1) \\ f(x = c_2) & d(c_2) \\ \vdots & \vdots \\ f(x = c_N) & d(c_N) \end{bmatrix}$$

Where

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

$$d(c_i) \equiv \text{ Sub-domain size}$$

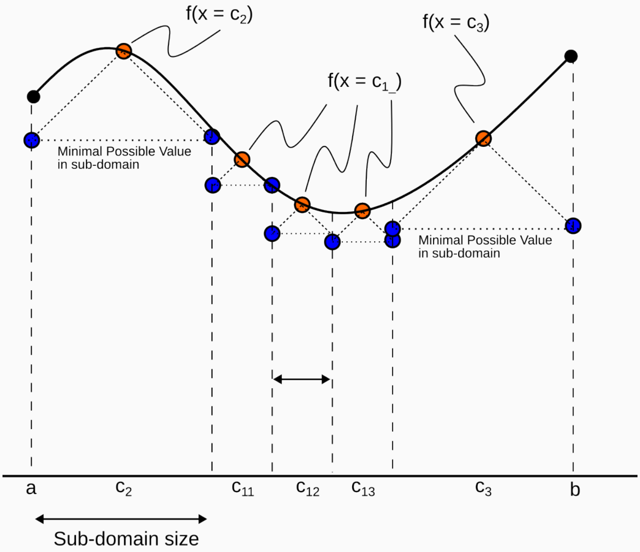
$$\text{for } i \in [1, N]$$



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



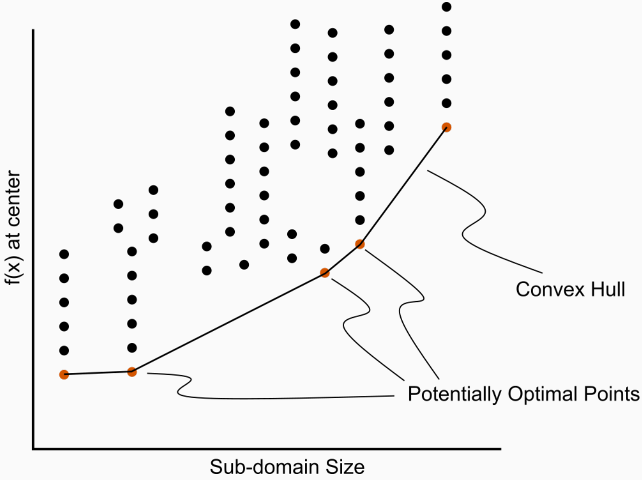
$$f(x = c_i) \equiv \text{Sampled function value}$$

$$d(c_i) \equiv \text{ Sub-domain size}$$

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

Determining Potentially Optimal Regions

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



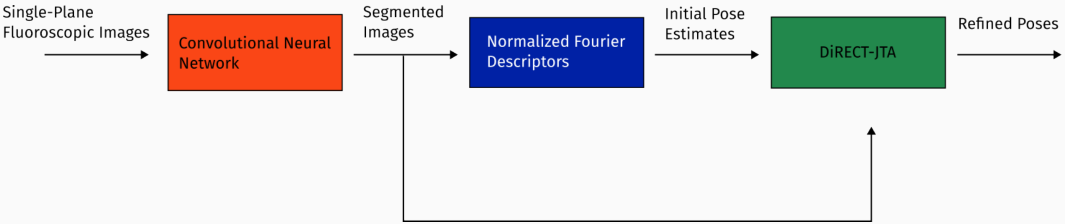
DiRECT for Joint Track Machine Learning

- 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 (*else*)	1

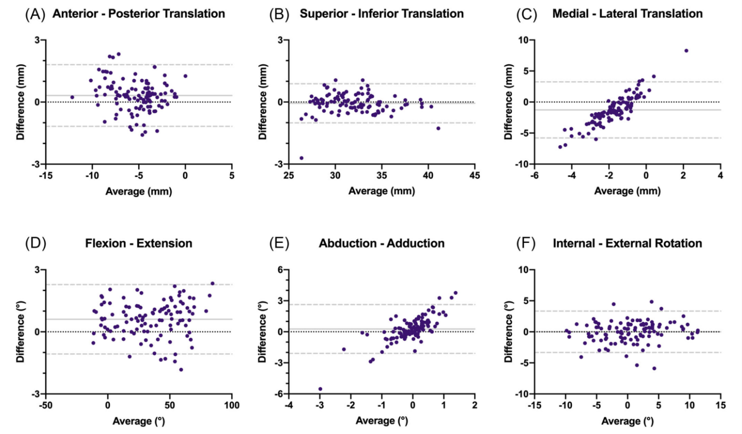
Testing Performance

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.

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.

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

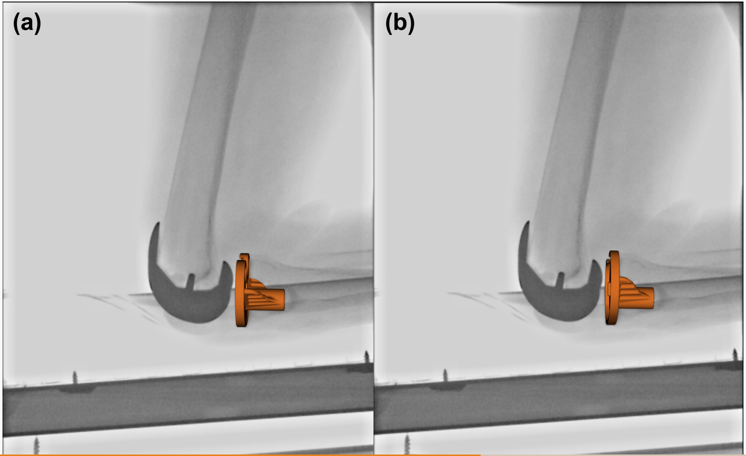
Where

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

Symmetry Traps

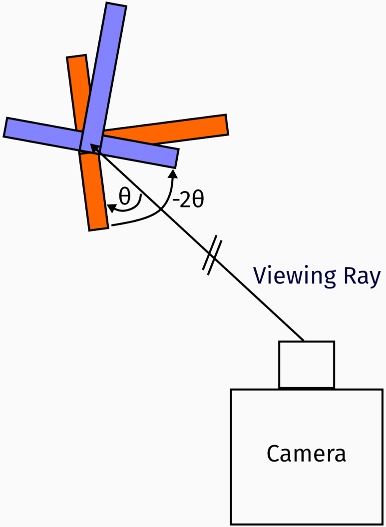
With a symmetric tibial implant, the contour is not always a perfect heuristic for true pose. Human operators typically utilize relative varus-valgus to determine correct pose.

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



Solving the Symmetric Pose

1. Create a vector from the camera origin to the implant origin (viewing ray).
2. Determine the axis ($\vec{m}$) and angle (θ) of rotation between the viewing ray and the symmetric (mediolateral) axis.
3. Rotate the implant -2θ about the same axis.
4. The final location is the symmetric pose of the object.



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

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

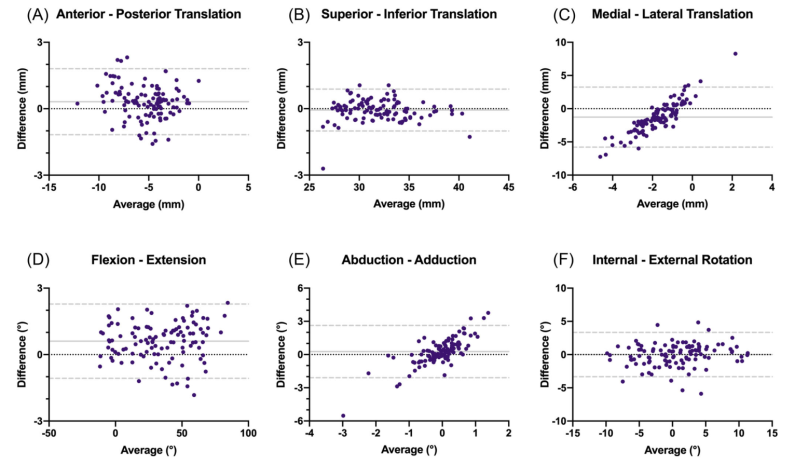
Binary Selection

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).

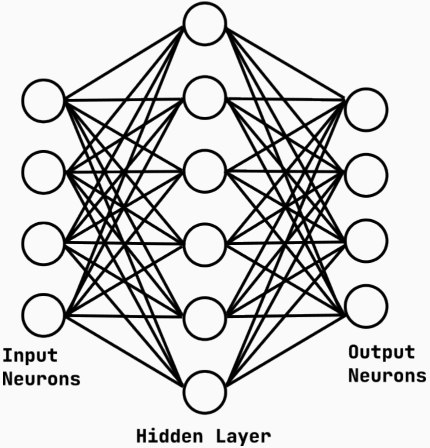
Bland-Altmann Calibration Constant

- 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

- 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.

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*.** 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.

[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

[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]`.

[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

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.

[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.

[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.

[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.

[8] C. Bradford Barber, David P. Dobkin, and Hannu Huhdanpaa. **"The Quickhull Algorithm for Convex Hulls"**. In: *ACM Transactions on Mathematical Software* 22.4 (Dec. 1996), pp. 469–483. ISSN: 0098-3500, 1557-7295. DOI: 10.1145/235815.235821.

[9] T. M. Chan. **"Optimal Output-Sensitive Convex Hull Algorithms in Two and Three Dimensions"**. In: *Discrete & Computational Geometry* 16.4 (Apr. 1996), pp. 361–368. ISSN: 0179-5376, 1432-0444. DOI: 10.1007/BF02712873.

[10] Henri A Vrooman et al. “**Fast and Accurate Automated Measurements in Digitized Stereophotogrammetric Radiographs**”. In: *Journal of Biomechanics* 31.5 (May 1998), pp. 491–498. ISSN: 00219290. DOI: 10.1016/S0021-9290(98)00025-6.

[11] M.R. Mahfouz et al. “**A Robust Method for Registration of Three-Dimensional Knee Implant Models to Two-Dimensional Fluoroscopy Images**”. In: *IEEE Transactions on Medical Imaging* 22.12 (Dec. 2003), pp. 1561–1574. ISSN: 0278-0062. DOI: 10.1109/TMI.2003.820027.

[12] B L Kaptein et al. “**Evaluation of Three Pose Estimation Algorithms for Model-Based Roentgen Stereophotogrammetric Analysis**”. In: *Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine* 218.4 (Apr. 2004), pp. 231–238. ISSN: 0954-4119, 2041-3033. DOI: 10.1243/0954411041561036.

[13] Tuuli Saari et al. “**Knee Kinematics in Medial Arthrosis. Dynamic Radiostereometry during Active Extension and Weight-Bearing**”. In: *Journal of Biomechanics* 38.2 (Feb. 2005), pp. 285–292. ISSN: 00219290. DOI: 10.1016/j.jbiomech.2004.02.009.

[14] P. N. Baker et al. **"The Role of Pain and Function in Determining Patient Satisfaction After Total Knee Replacement: Data From the National Joint Registry for England and Wales".** In: *The Journal of Bone and Joint Surgery. British volume* 89-B.7 (July 2007), pp. 893–900. ISSN: 0301-620X, 2044-5377. DOI: 10.1302/0301-620X.89B7.19091.

[15] Steven Kurtz et al. **"Projections of Primary and Revision Hip and Knee Arthroplasty in the United States from 2005 to 2030:"** in: *The Journal of Bone & Joint Surgery* 89.4 (Apr. 2007), pp. 780–785. ISSN: 0021-9355. DOI: 10.2106/JBJS.F.00222.

[16] Bo Gao and Naiquan (Nigel) Zheng. **"Investigation of Soft Tissue Movement during Level Walking: Translations and Rotations of Skin Markers".** In: *Journal of Biomechanics* 41.15 (Nov. 2008), pp. 3189–3195. ISSN: 00219290. DOI: 10.1016/j.jbiomech.2008.08.028.

[17] Robert B. Bourne et al. **"Patient Satisfaction after Total Knee Arthroplasty: Who Is Satisfied and Who Is Not?"** In: *Clinical Orthopaedics & Related Research* 468.1 (Jan. 2010), pp. 57–63. ISSN: 0009-921X. DOI: 10.1007/s11999-009-1119-9.

[18] C. E. H. Scott et al. **"Predicting Dissatisfaction Following Total Knee Replacement: A Prospective Study of 1217 Patients".** In: *The Journal of Bone and Joint Surgery. British volume* 92-B.9 (Sept. 2010), pp. 1253–1258. ISSN: 0301-620X, 2044-5377. DOI: 10.1302/0301-620X.92B9.24394.

[19] Mei-Ying Kuo et al. **"Influence of Soft Tissue Artifacts on the Calculated Kinematics and Kinetics of Total Knee Replacements during Sit-to-Stand".** In: *Gait & Posture* 33.3 (Mar. 2011), pp. 379–384. ISSN: 09666362. DOI: 10.1016/j.gaitpost.2010.12.007.

[20] John C. Ivester et al. **"A Reconfigurable High-Speed Stereo-Radiography System for Sub-Millimeter Measurement of In Vivo Joint Kinematics".** In: *Journal of Medical Devices* 9.4 (Dec. 2015), p. 041009. ISSN: 1932-6181, 1932-619X. DOI: 10.1115/1.4030778.

[21] Cheng-Chung Lin et al. **"Effects of Soft Tissue Artifacts on Differentiating Kinematic Differences between Natural and Replaced Knee Joints during Functional Activity".** In: *Gait & Posture* 46 (May 2016), pp. 154–160. ISSN: 09666362. DOI: 10.1016/j.gaitpost.2016.03.006.

[22] Charles Audet and Warren Hare. ***Derivative-Free and Blackbox Optimization.*** Springer Series in Operations Research and Financial Engineering. Cham: Springer International Publishing, 2017. ISBN: 978-3-319-68912-8 978-3-319-68913-5. DOI: 10.1007/978-3-319-68913-5.

[23] Ashish Vaswani et al. ***Attention Is All You Need.*** Dec. 2017. arXiv: arXiv:1706.03762.

[24] P. D. L. Flood and Scott A. Banks. **"Automated Registration of 3-D Knee Implant Models to Fluoroscopic Images Using Lipschitzian Optimization".** In: *IEEE Transactions on Medical Imaging* 37.1 (2018), pp. 326–335. DOI: 10.1109/tmi.2017.2773398.

[25] Alexander Buslaev et al. **"Albumentations: Fast and Flexible Image Augmentations".** In: *Information* 11.2 (Feb. 2020), p. 125. ISSN: 2078-2489. DOI: 10.3390/info11020125.

[26] Nicolas Carion et al. **"End-to-End Object Detection with Transformers".** In: (2020), pp. 213–229. DOI: 10.1007/978-3-030-58452-8_13.

[27] Jingdong Wang et al. **"Deep High-Resolution Representation Learning for Visual Recognition".** In: *arXiv:1908.07919 [cs]* (Mar. 2020). arXiv: 1908.07919 [cs].

[28] Ishan Bajaj, Akhil Arora, and M. M. Faruque Hasan. **“Black-Box Optimization: Methods and Applications”.** In: (Jan. 2021), pp. 35–65. DOI: 10.1007/978-3-030-66515-9_2.

[29] 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.

[30] Alexey Dosovitskiy et al. ***An Image Is Worth 16x16 Words: Transformers for Image Recognition at Scale.*** June 2021. arXiv: arXiv:2010.11929.

[31] Meng-Hao Guo et al. **“Attention Mechanisms in Computer Vision: A Survey”.** In: *arXiv: Computer Vision and Pattern Recognition* (Nov. 2021).

[32] 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].

[33] 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.

[34] S. Zuffi et al. **“A Model-Based Method for the Reconstruction of Total Knee Replacement Kinematics”.** In: *IEEE Transactions on Medical Imaging* 18.10 (Oct./1999), pp. 981–991. ISSN: 02780062. DOI: 10.1109/42.811310.