

Joint Track Machine Learning

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March 9, 2023

Outline

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Aim 1 - Joint Track Machine Learning

Aim 2 - Overcoming Single-Plane Limitations

Aim 3 - Pilot Human Study

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Aim 5 - Joint Track Auto Toolkit

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Introduction

Acknowledgments

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

Motivation

The Problem

- By 2030, roughly 3.5 million Total Knee Arthroplasty (TKA) will be performed in the US [18].
- 20% of patients receiving TKA are dissatisfied.
 - Instability, pain, unnatural [3, 5, 24].
- No reliable method of clinically assessing and quantifying joint dynamics.
 - Too much human supervision, too time consuming



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**.



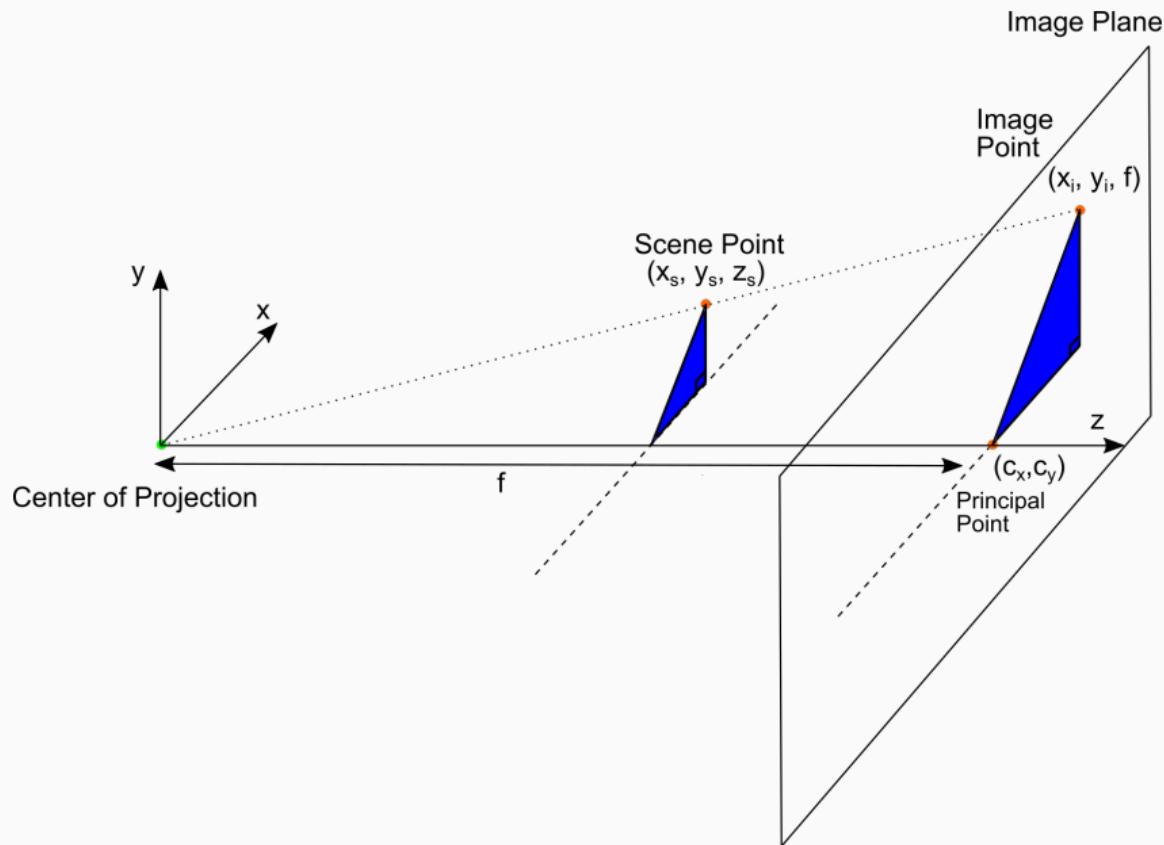
Constraints

- 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.



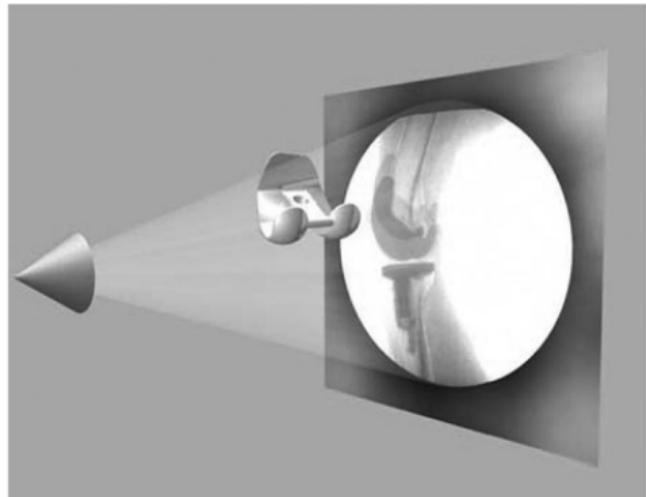
Background

Projective Geometry



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 [22]

Historical Methods

Overview

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

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

Pre-Computed Projections

- Saving space and memory by pre-computing as much as possible.
- Pre-computed distance maps [30, 20].
- Pre-computed shape libraries [4]

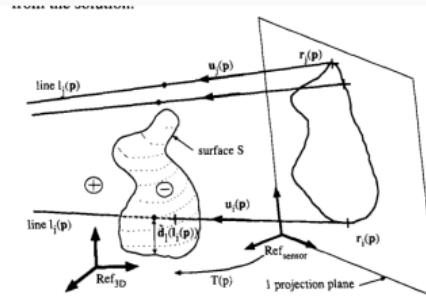
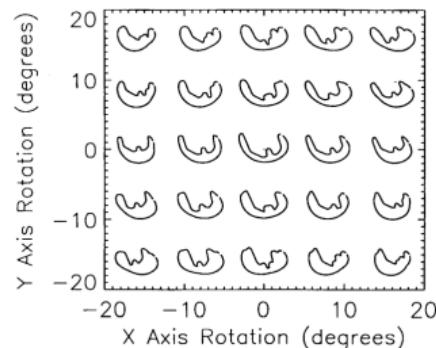


Fig. 2. Projection line to surface distance computation.

From [20]



From [4]

Limitations of Pre-Computed Projections

- Requires an accurate contour from the input image in order to perform calculations.

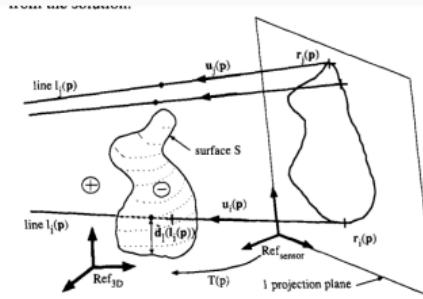
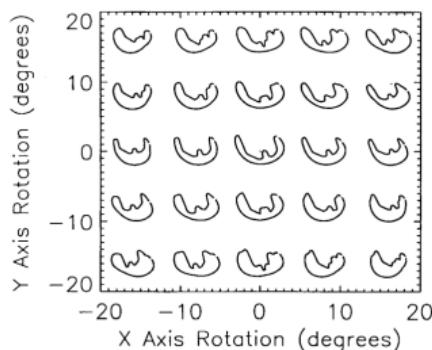


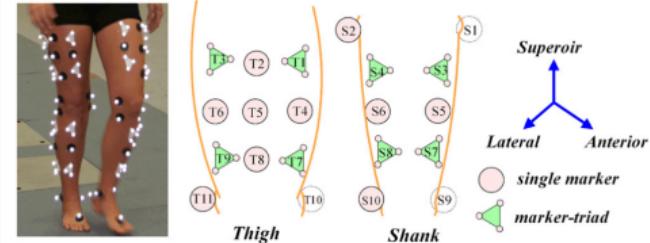
Fig. 2. Projection line to surface distance computation.

From [20]



From [4]

Motion Capture (MoCap)



From [12]

- Can measure motion of MoCap beads very accurately.
- Skin-mounted [12, 17, 21].
- Bone pins [19] (any volunteers?).



From [19]

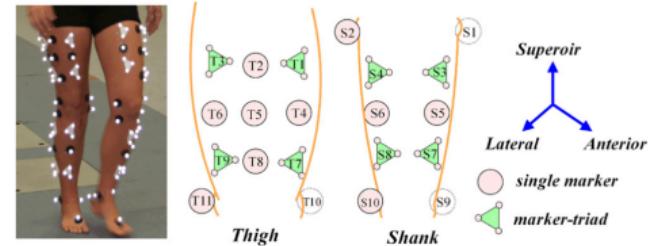
Limitations of Motion Capture

Skin Mounted

- Doesn't accurately describe underlying skeletal motion with clinical accuracy [12, 17, 21].

Bone Pins

- Bone Pins
- Need I say more?



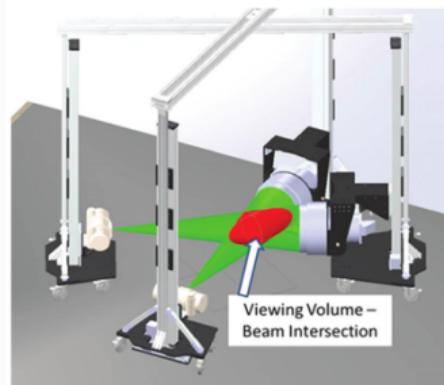
From [12]



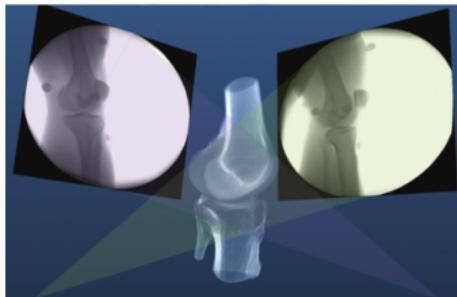
From [19]

Biplane Imaging

- Utilizes multiple cameras to resolve 3D position and orientation[14, 7].
 - Highly accurate.
 - Gold Standard.

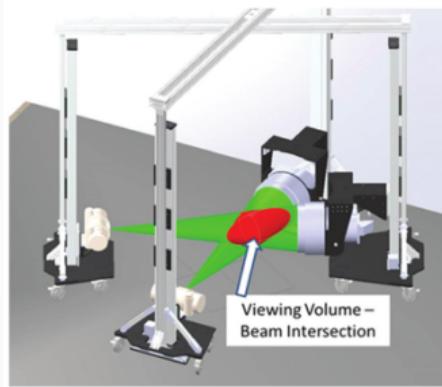


Both from [14]

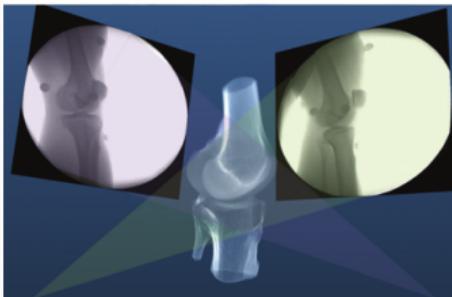


Limitations of Biplane Imaging

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

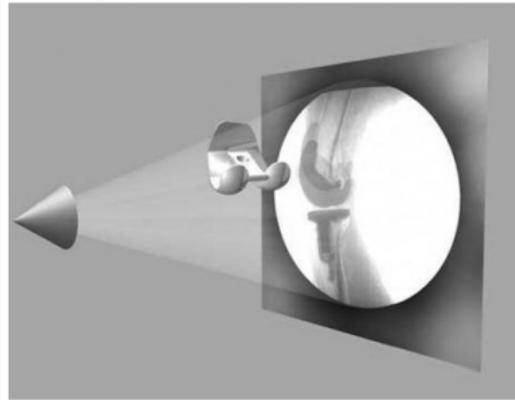


Both from [14]



Iterative Projections

- Take advantage of modern computational graphics pipelines to quickly perform projection matching.
 - Image/Intensity similarity metrics [22]
 - Feature/Contour similarity metrics [11]



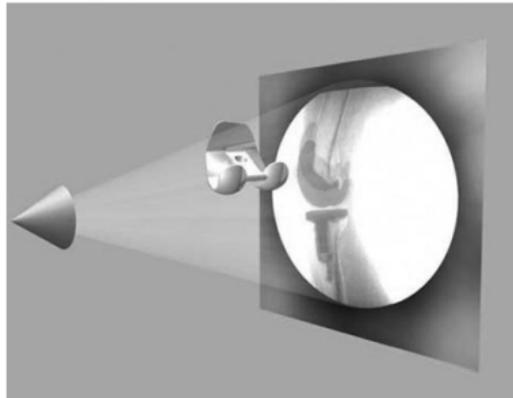
From [22]



From [11]

Limitations of (historic) Iterative Projection Methods

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



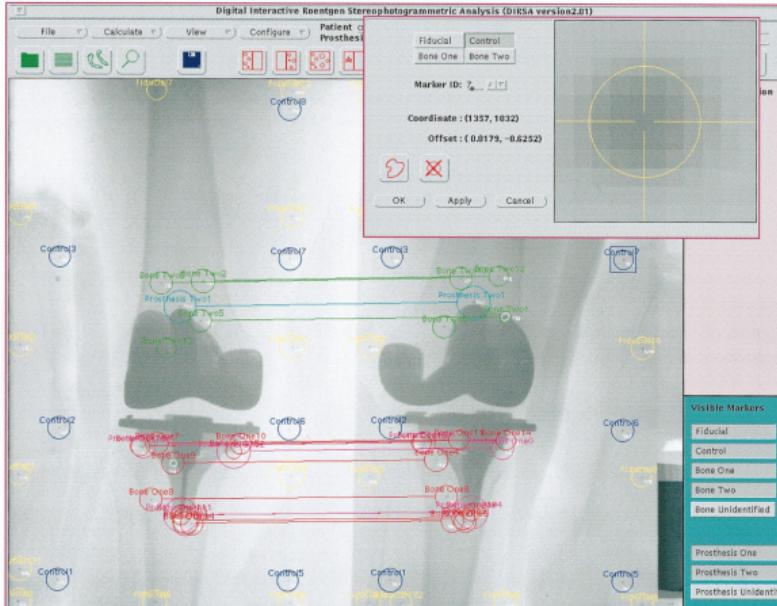
From [22]



From [11]

Roentgen Stereophotogrammetry (RSA)

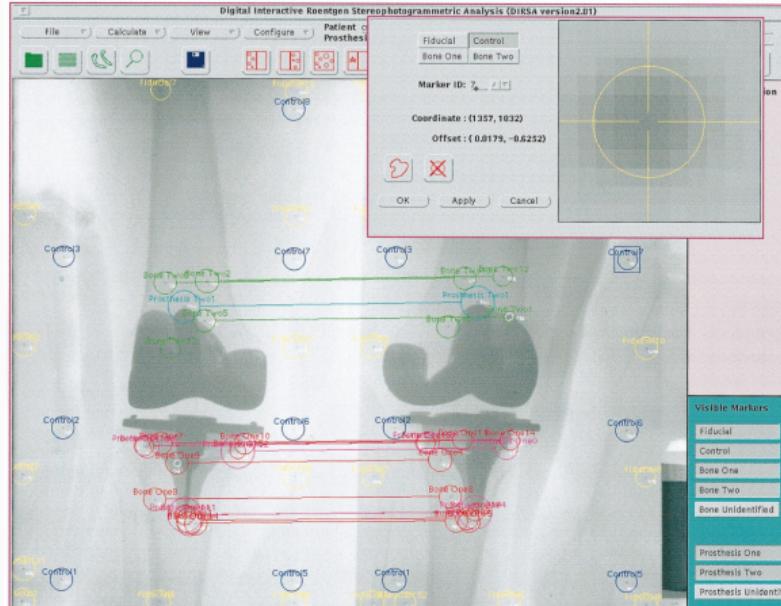
- Uses implanted tantalum beads for motion tracking [28, 25]
- Extremely accurate [16, 23]
- Gold standard Measurement [6]



From [28]

Limitations of RSA

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



From [28]

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

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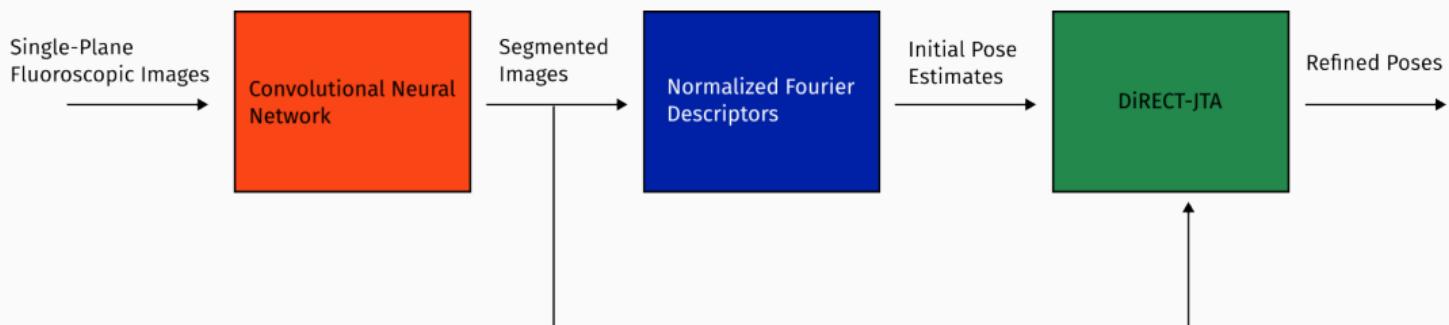
References

Goal

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

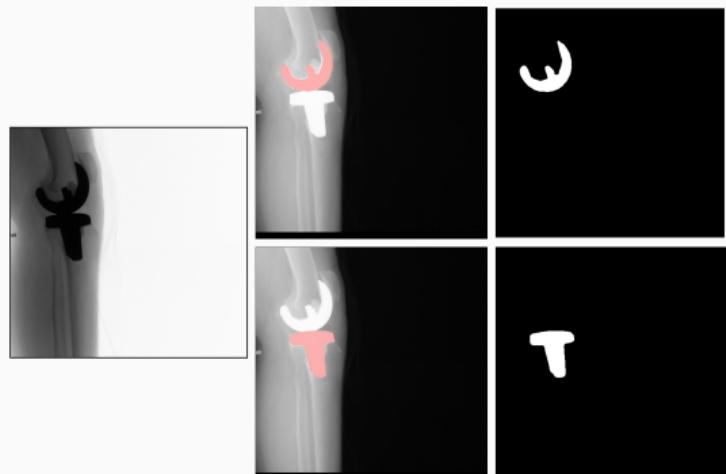
Method

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



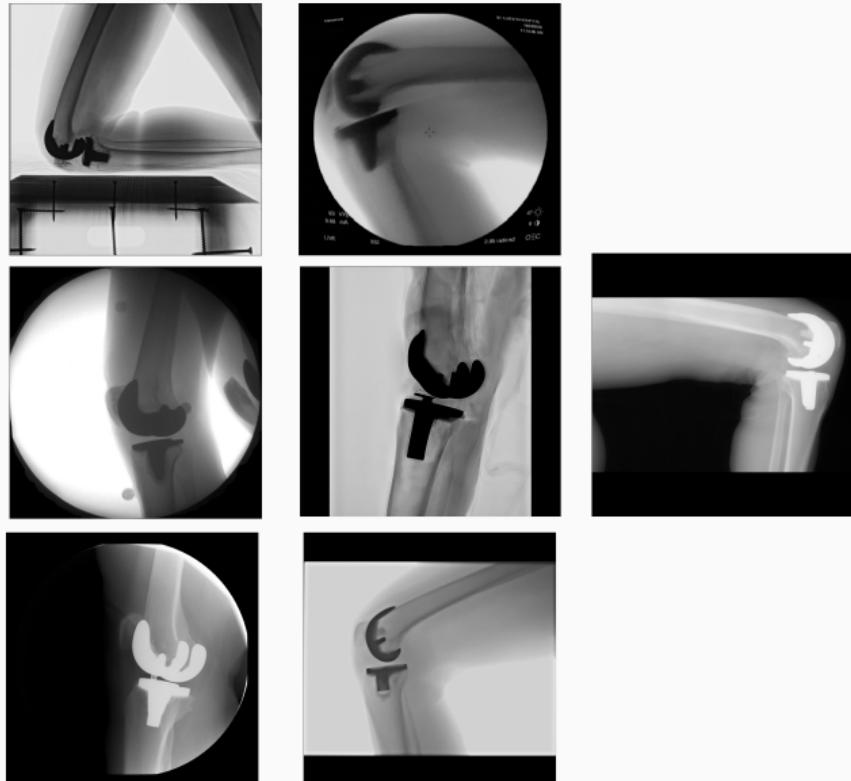
Autonomous Implant Detection Using Convolutional Neural Networks

- 2 CNNs
 - Femoral and Tibial implants
- High Resolution Network [29]



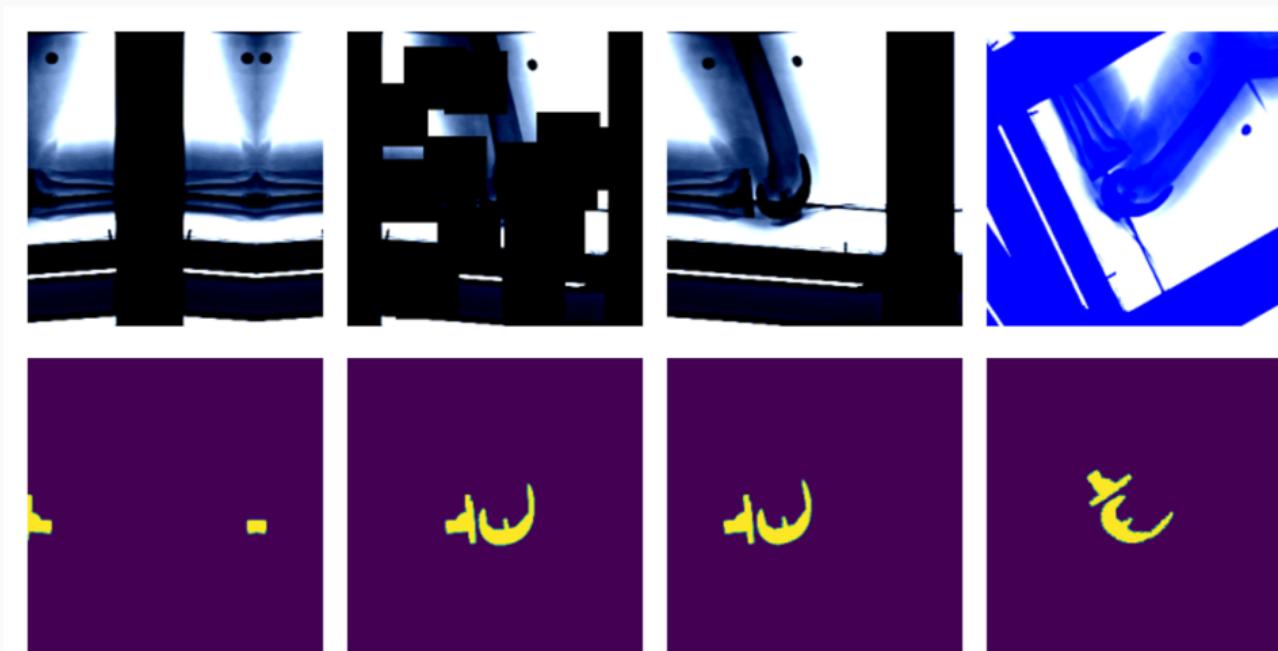
Neural Network Data

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



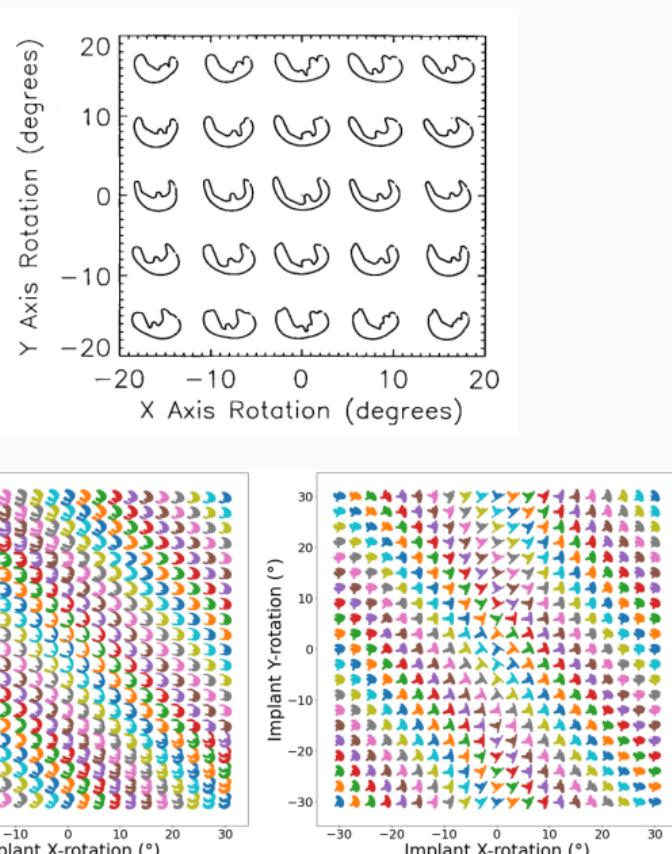
Neural Network Robustness

- Additional augmentations introduced during training [8].



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.

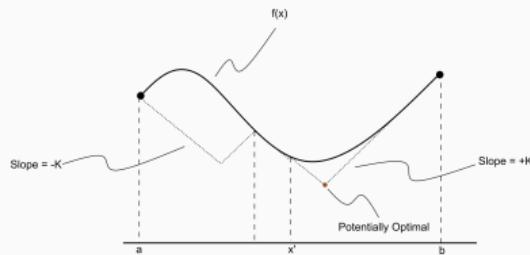
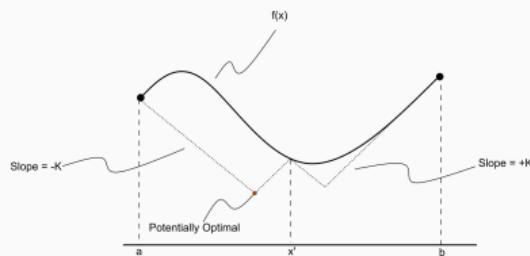
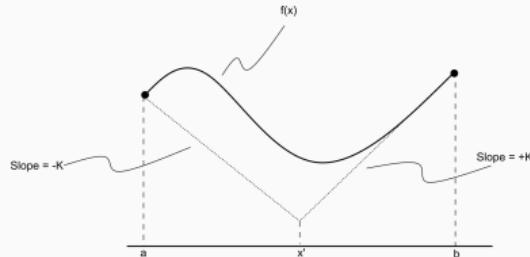


Optimization Routine

- No analytic form of the objective function exists, it **must** be sampled at points of interest.
 - Black Box Optimization [1, 2]

Lipschitzian Optimization

- Robust, global, black-box optimization routine if Lipschitz constant (K) is known [26].
- Lipschitz constant bounds the rate of change of a function.
- What if you don't know the Lipschitz constant?

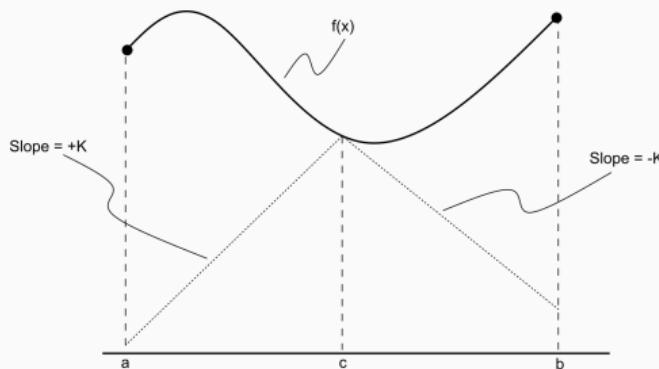


Lipschitzian Optimization without the Lipschitz Constant

Lipschitzian Optimization Without the Lipschitz Constant

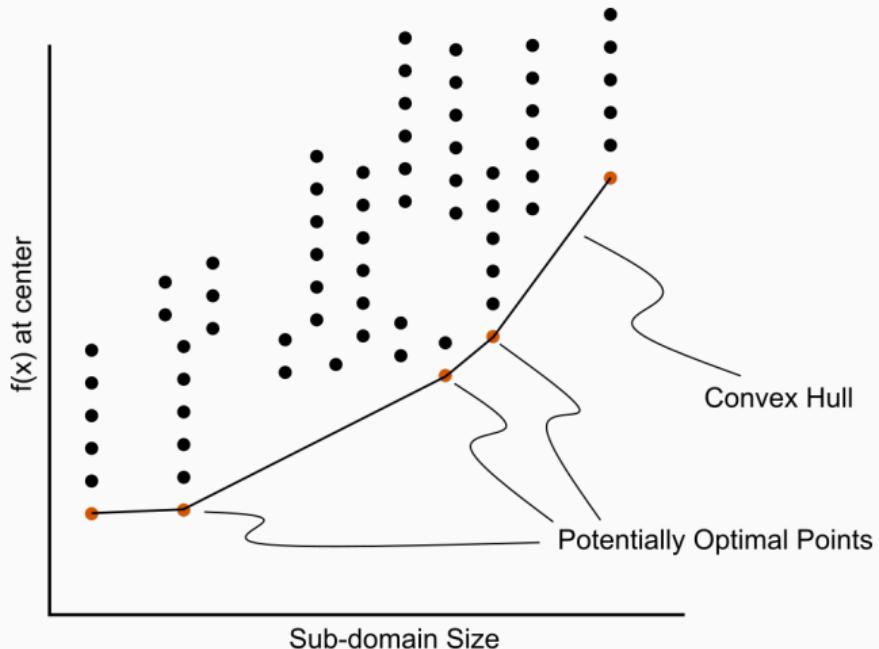
D. R. JONES,¹ C. D. PERTTUNEN,² AND B. E. STUCKMAN³

- 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



Determining Potentially Optimal Regions

- Convex hull of region size vs. center value



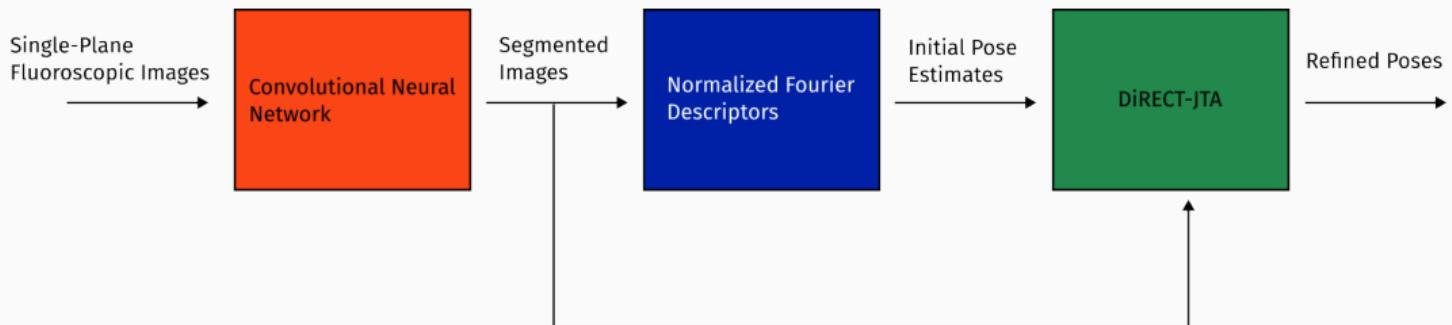
DiRECT for Joint Track Machine Learning

- 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

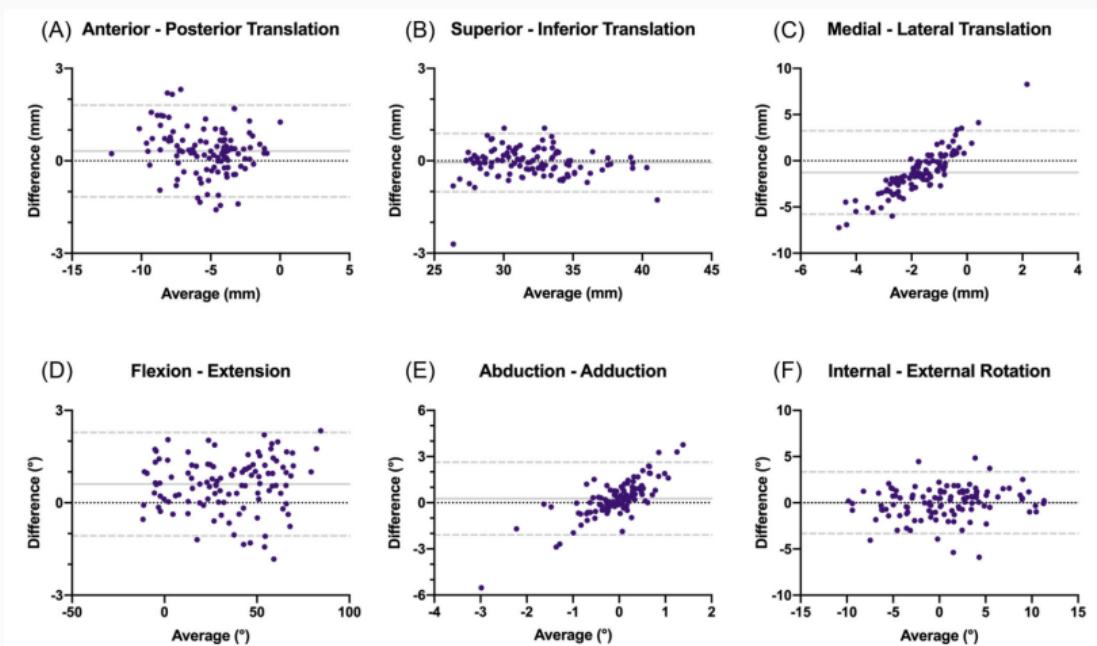
Testing Performance

Now that we have our refined poses, how well does out 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 [6, 15].



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.



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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.

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

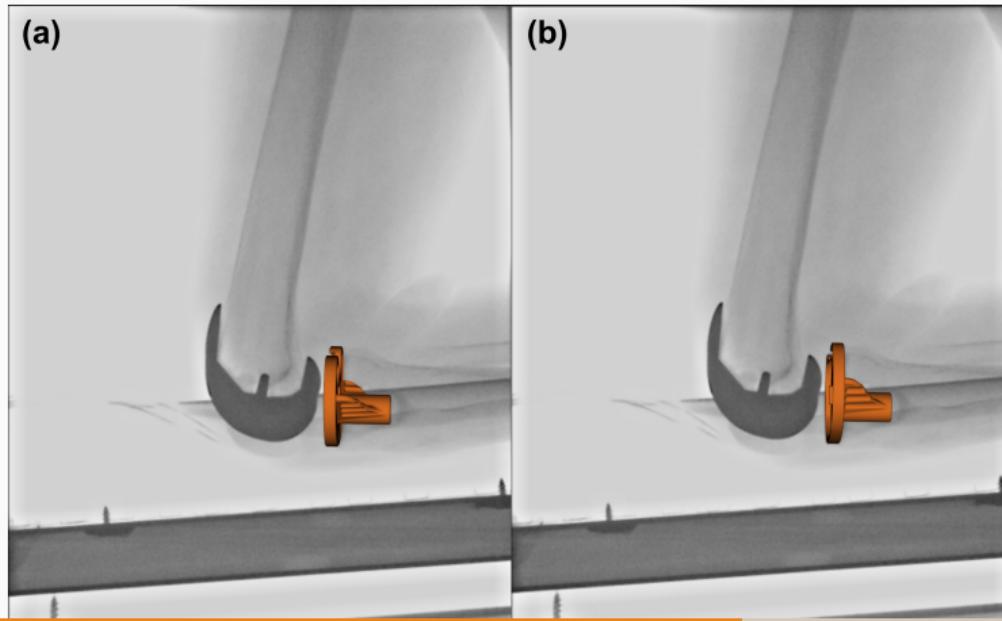
Where

$ML \equiv$ 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 [15].



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.

Five Approaches

- Virtual ligaments
- Binary selection between two poses
- Bland-Altman Calibration Constant
- Random Forest
- 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

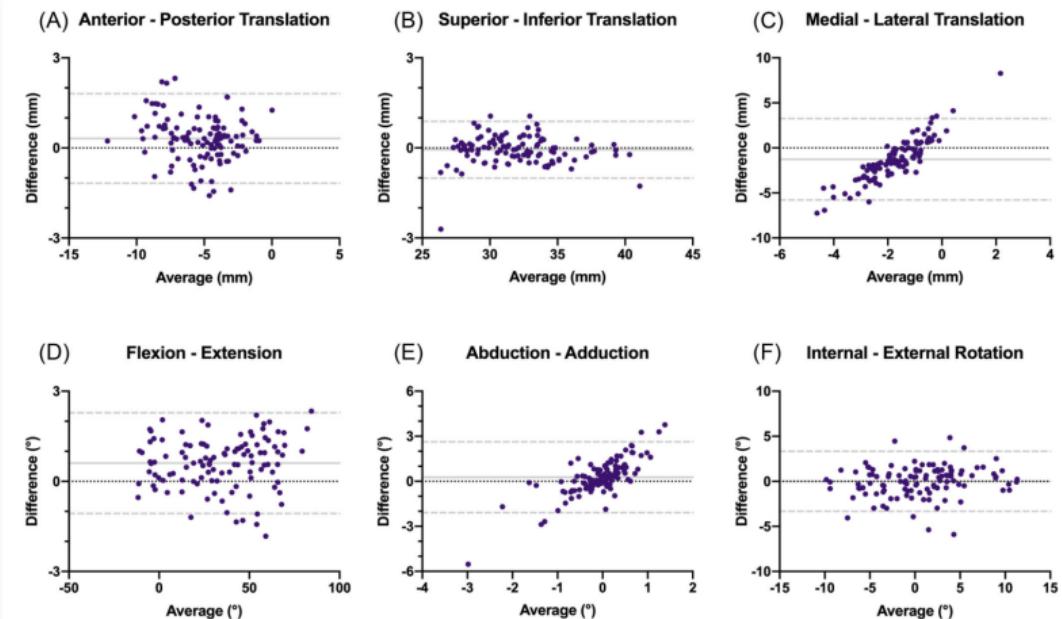
Binary Selection

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).

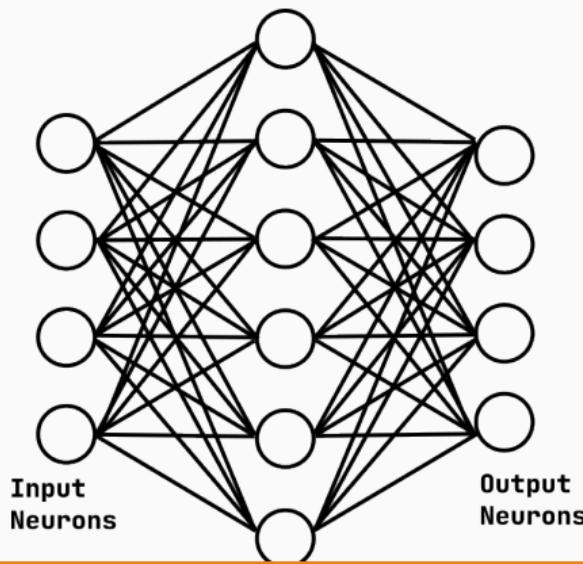
Bland-Altman Calibration Constant

- 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
- Pending Methods
 - Binary Selection
 - Bland-Altman Calibration
 - Fully Connected Network

Journal paper will be ready for submission by June.

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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.

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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 [9, 27, 13, 10] (“translating” movements into outcomes and other movements)

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Goal

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.

References

References

- [1] 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.
- [2] 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.
- [3] 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.

References ii

- [4] 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.
- [5] 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.
- [6] 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.
- [7] 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.
- [8] 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.

- [9] 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.
- [10] Alexey Dosovitskiy et al. *An Image Is Worth 16x16 Words: Transformers for Image Recognition at Scale*. June 2021. arXiv: arXiv:2010.11929.
- [11] 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.
- [12] 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.
- [13] Meng-Hao Guo et al. “**Attention Mechanisms in Computer Vision: A Survey**”. In: *arXiv: Computer Vision and Pattern Recognition* (Nov. 2021).

- [14] 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.
- [15] 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].
- [16] 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.
- [17] 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.

- [18] 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.
- [19] 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.
- [20] 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.
- [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] 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.
- [23] Tuuli Saari et al. “Knee Kinematics in Medial Arthroscopy. 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.
- [24] 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.
- [25] 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.

- [26] 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>.
- [27] Ashish Vaswani et al. ***Attention Is All You Need***. Dec. 2017. arXiv: arXiv:1706.03762.
- [28] 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.
- [29] Jingdong Wang et al. “**Deep High-Resolution Representation Learning for Visual Recognition**”. In: *arXiv:1908.07919 [cs]* (Mar. 2020). arXiv: 1908.07919 [cs].
- [30] 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.