Joint Track Machine Learning

Andrew Jensen

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Outline

Introduction

Acknowledgments

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

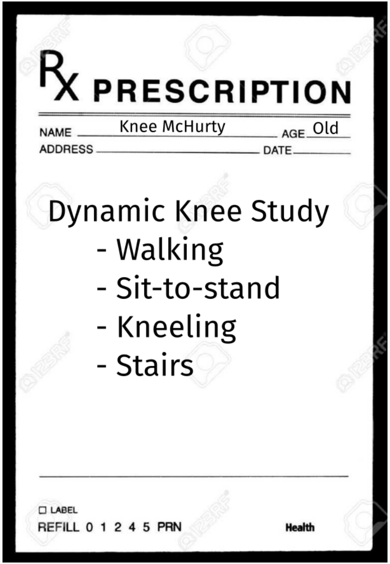
Motivation

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

Translation

$$\begin{pmatrix} v'_x \\ v'_y \end{pmatrix} = \begin{pmatrix} v_x \\ v_y \end{pmatrix} + \begin{pmatrix} t_x \\ t_y \end{pmatrix}$$

$$\rightarrow$$

$$\begin{pmatrix} v'_x \\ v'_y \\ 1 \end{pmatrix} = \begin{pmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} v_x \\ v_y \\ 1 \end{pmatrix}$$

Rigid Body Transformations

Rotations

$$R_x = \begin{pmatrix} 1 & 0 & 0 \\ 0 & c_x & -s_x \\ 0 & s_x & c_x \end{pmatrix}$$

$$R_y = \begin{pmatrix} s_y & 0 & c_y \\ 0 & 1 & 0 \\ c_y & 0 & -s_y \end{pmatrix}$$

$$R_z = \begin{pmatrix} c_z & -s_z & 0 \\ s_z & c_z & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

Homogeneous Transformation Matrices

$$\begin{aligned}\tilde{\vec{v}}' &= \begin{pmatrix} & \mathrm{R}_{3\times 3} & & \vec{t}_{3\times 1} \\ 0 & 0 & 0 & 1 \end{pmatrix} \tilde{\vec{v}} \\ &= T_B^A \tilde{\vec{v}}\end{aligned}$$

Now we have a notation that allows us to describe arbitrary movement between reference frames.

Projective Geometry

$$\begin{pmatrix} x_s \\ y_s \\ z_s \\ 1 \end{pmatrix}_i = T_{scene}^{cam} \tilde{\mathrm{p}}_{\mathrm{i}}^{\mathrm{obj}}$$

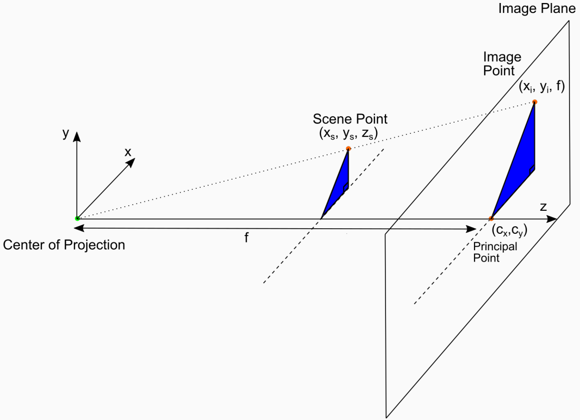
$$\begin{pmatrix} \tilde{x}_{img} \\ \tilde{y}_{img} \\ \tilde{z} \end{pmatrix} = \begin{pmatrix} f & 0 & 0 \\ 0 & f & 0 \\ 0 & 0 & 1 \end{pmatrix} \vec{x}_s$$

Where

$$x_{img} = \frac{\tilde{x_{img}}}{\tilde{z}} = \frac{f}{z_s} x_s$$

$$y_{img} = \frac{\tilde{y_{img}}}{\tilde{z}} = \frac{f}{z_s} y_s$$

Note: We are still in the camera's reference frame



Pixel Coordinates

Convert camera coordinates into image coordinates.

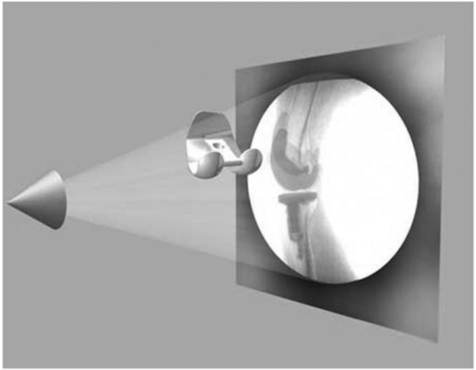
$$p_x = k_x x_{img} + c_x$$
$$p_y = k_y y_{img} + c_y$$

Where

$$k \equiv \text{ Pixel Spacing}$$
$$c \equiv \text{ Image Focal Point}$$

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]

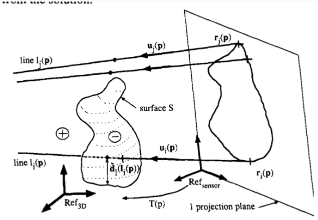
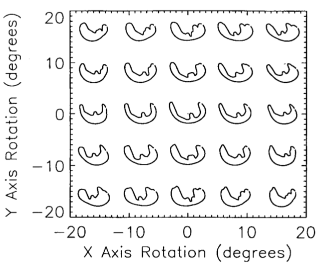


Fig. 2. Projection line to surface distance computation.

From [20]

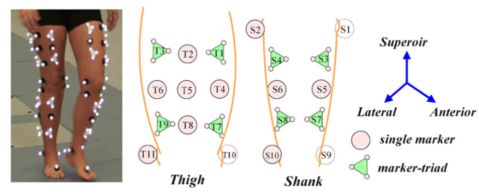


From [4]

Limitations of Pre-Computed Projections

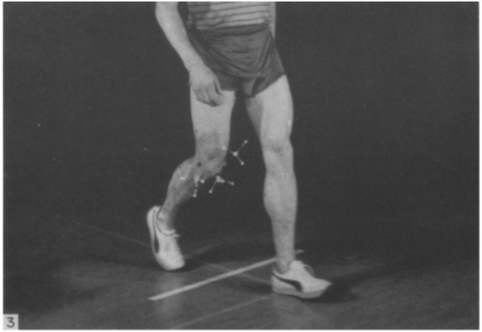
- Requires an accurate contour from the input image in order to perform calculations.
    - Human supervision vs. inaccuracy.

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

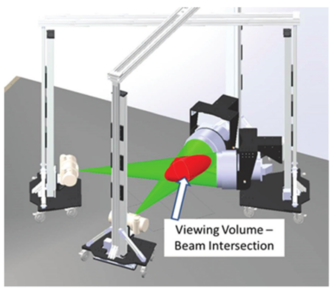
- Doesn't accurately describe underlying skeletal motion with clinical accuracy [12, 17, 21].

Bone Pins

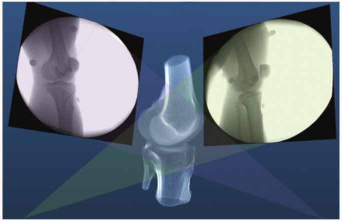
- Bone Pins
- Need I say more?

Biplane Imaging

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



Both from [14]

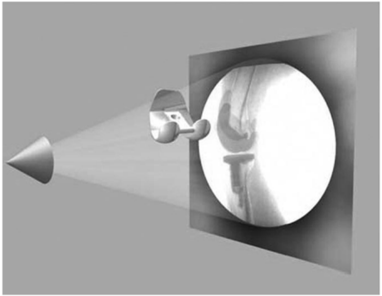


Limitations of Biplane Imaging

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

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]

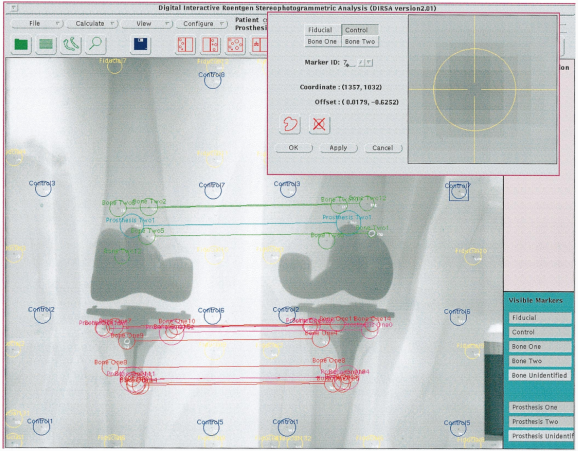
From [11]

Limitations of (historic) Iterative Projection Methods

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

Model-based Roentgen Stereophotogrammetry (MBRSA)

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



From [28]

Limitations of MBRSA

- Involves additional surgical procedures for inserting tantalum beads
- Human supervision
- Typically requires bi-plane imaging.

Aims

Aims

Aims 1/2
Joint Track Machine Learning and Overcoming Single-Plane Limitations

Aim 3/4
Pilot Trials and Standardized Kinematics Exam

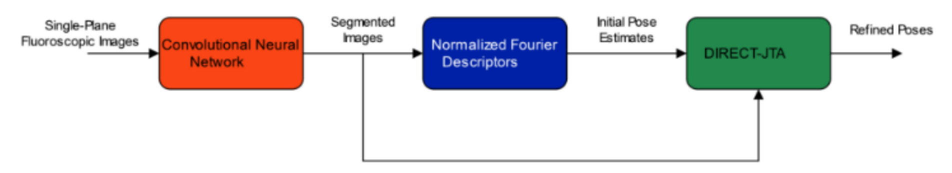
Aim 5
Joint Track Auto Toolkit

Goal

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

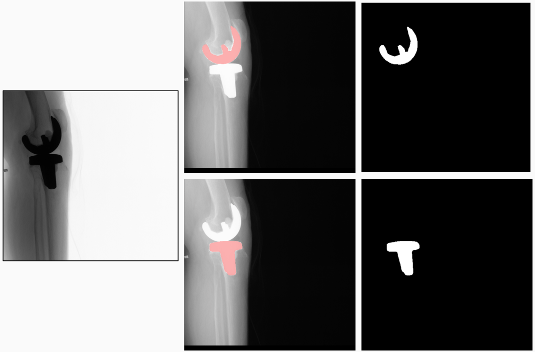
Method

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



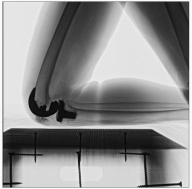
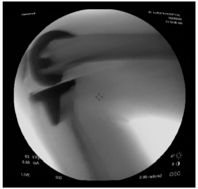
Autonomous Implant Detection Using Convolutional Neural Networks

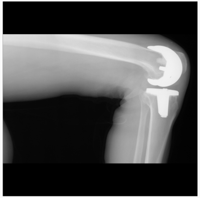
- 2 CNNs
    - Femoral and Tibial implants
- High Resolution Network [29]



Neural Network Data

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

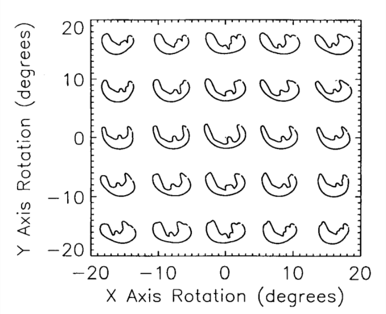



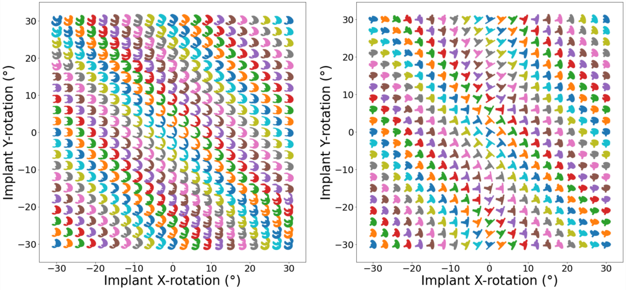



- Additional augmentations introduced during training [8].

Normalized Fourier Descriptor Shape Libraries

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





Pose Refinement Using Global Optimization

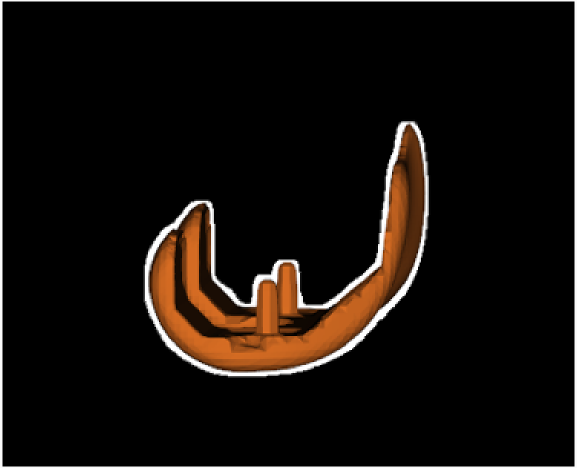
- Two main features
  - Objective function
  - Optimization routine

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

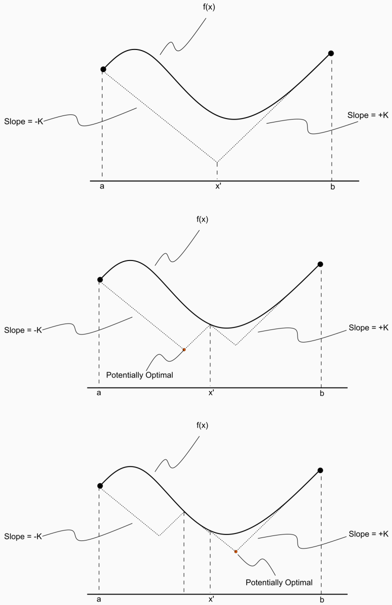
- Dilation decreases sensitivity to perturbations.
- Multi-stage optimization can reduce dilation back to original edges.

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?

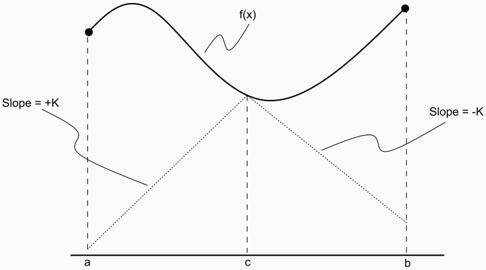


Lipschitzian Optimization without the Lipschitz Constant

Lipschitzian Optimization
Without the Lipschitz Constant

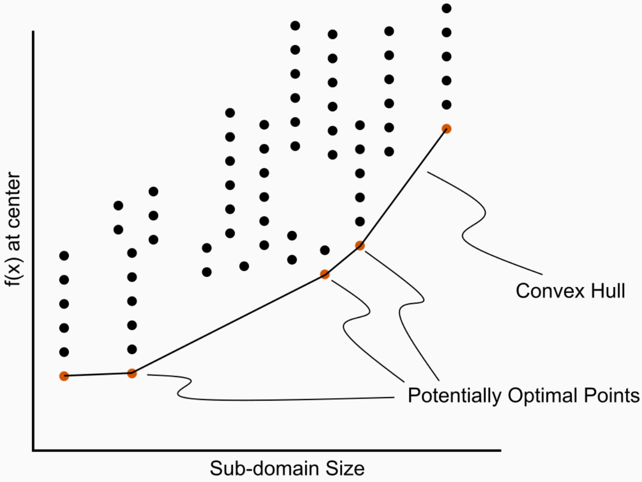
D. R. Jones,[1] C. D. Perttunen,[2] and B. E. Stuckman[3]

- 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



Determining Potentially Optimal Regions

- Convex hull of region size vs. center value



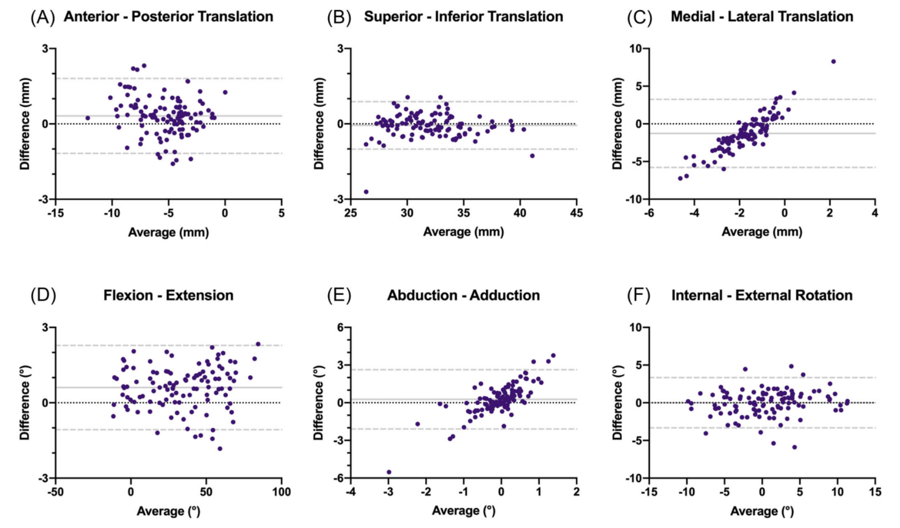
DiRECT for Joint Track Machine Learning

- 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 (*else*)	1

Validation

- 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.

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.

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

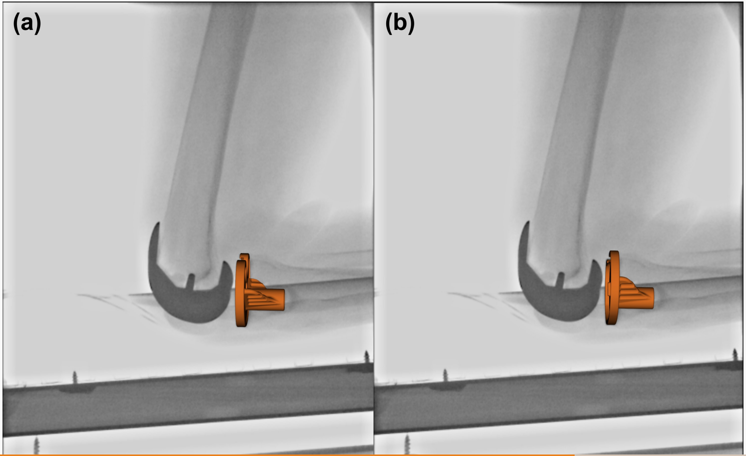
Where

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

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 [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-Altmann Calibration Constant
- Random Forest
- Fully Connected Network

Virtual Ligaments

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

Where

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

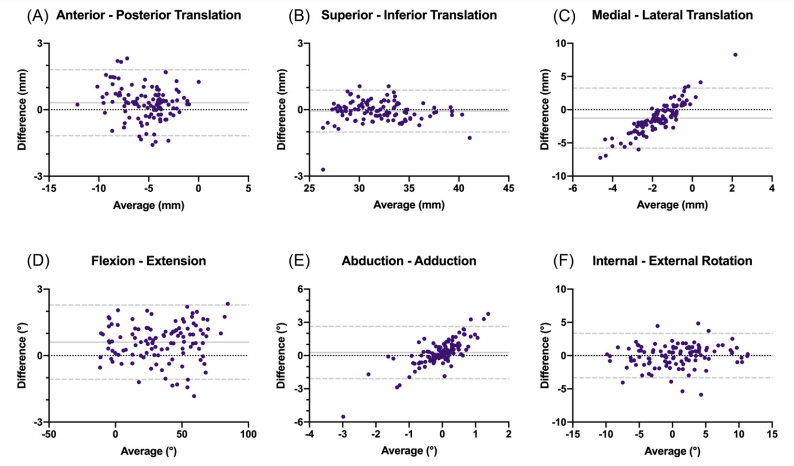
Binary Selection

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).

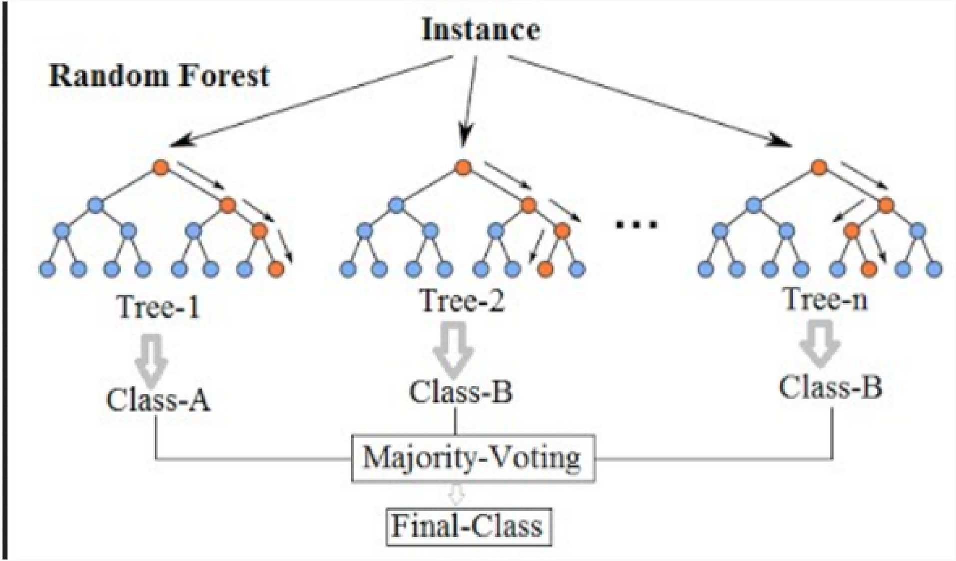
Bland-Altmann Calibration Constant

- 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.



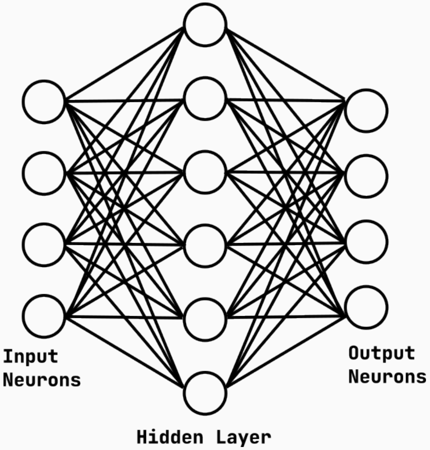
Random Forest

Train a random forest with femoral implant pose and both symmetric tibial poses.



Fully Connected Network

- Encode symmetric pose calculation into FCN.
- Feed femoral and tibial pose into network.
    - “Keep” or “Switch”



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

Goal

Anatomically and statistically determine the highest yield movements to measure to establish a “standard kinematics exam”.

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 questions, rather than fiddling with annoying software.

Method

- Consult with clinicians and researchers to determine wide ranging motions and static poses.
- Utilize statistical methods to determine covariance and causal/corollary relationships.
    - Clustering
    - Transformers [9, 27, 13, 10] ("translating" movements into outcomes and other movements)

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.

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