Understanding Knee Joint Kinematics using MRI

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Abstract— **This project aims to develop the framework for a predictive model for the knee joint by using landmarks on the femur and the tibia. Knee MRI data was segmented using Slicer 3D. Segments were imported into Python as point cloud data and key landmarks were identified by a deep learning algorithm which predicted landmark position with an RMSE between 7mm and 11mm. Alignment of axes to the principal components of the segments was completed using principal component analysis. This project serves as a foundation for a predictive kinematic model based on MRI data input.**

I. INTRODUCTION

Knee braces are used extensively in sports, rehabilitation, and as a surgery alternative in some cases. Their uses vary from injury prevention, to providing additional stability, to limit extracurricular motion in patients with ligament damage.[1] However, the current knee brace technology revolves around a simplified pin joint model of the knee which is rarely anatomically correct. This can lead to restricted gait in recovering patients and decreased mobility in active settings. This research aims to develop a more realistic model which predicts knee joint kinematics based on patient MRI imaging.

II. BACKGROUND

A. MRI and Characterization

Magnetic Resonance Imaging (MRI) is a technique that uses strong magnetic fields to scan the body and render detailed images of the tissues inside.[2] The data collected can then be analyzed using specialized software to isolate the tissues in any part of the body (brain matter, bones and joints, muscle tissue, organs) as it best fits the user's intent. The focus of this project will be to collect MRI scans of the femur and tibia bones at different angles and orientations. This data will be used as the foundation for our joint landmark characterization and joint bio-kinematics modeling.

B. Knee Joint Kinematics

In the past, several knee exoskeleton and prosthetic designs simplified the knee kinematics to a 1 degree-of-freedom pin-joint motion. This simplification is not ideal as the knee can have up to 6 degrees of freedom as well as a rolling and grinding motion.[3] In the last decade, researchers have found new and innovative ways of approaching knee kinematics using MRI scans and software to find the mathematical relation between the knee joints. A study conducted in 2010 used MRI data to compare three different models of knee kinematics.[4] The model that simplified the femur and tibia contact points into one stationary ellipse as the tibia and a rolling eclipse to represent the femur showed the highest model accuracy. This study provided a strong foundation for general 2 degrees of freedom mathematical modeling of joint kinematics. This project intends to model the knee joint kinematics to better reflect actual knee bio-kinematics using MRI scans as opposed to cadaver simulations. This modeling can serve as a basis to further improve the design of prosthetics, robotics, and exoskeletons by providing realistic bio-inspired mechanics.

III. PROJECT GOALS

The objective of this project is to create a basis for a knee kinematic anatomical landmark predictive model that outputs repeatable landmarks as well as the axis of operation of the femur and tibia when given an STL model of the bone. To accomplish this objective, four main goals were created.

A. Expected Goals:

- Segment and Analyze MRI data: We will analyze the MRI images and segment the femur and tibia

into stereo-lithography STL files for further analysis.
- Determine the principal axes along the tibia and femur: Use Matlab software to generate these principal axes to create a new frame of reference along the bones.
- Identify landmarks: Use deep learning to automatically predict key landmarks from segmented MRI point cloud data. Verify accuracy by comparing deep learning selection to manual selection
- Develop a Predictive Model for landmark identification: Create a Matlab operation that inputs a collection of knee models at different angles and outputs a series of anatomical landmarks on the femur and the tibia.

B. Reach Goal:

- Extrapolate our model to other joints: If we are able to achieve our expected goals, we would like to extend our model to predict kinematics of other joints as well.

IV. METHODS

A. Scan Segmentation

Our primary approach would be to use Slicer to segment the required region in the images. Segmentation of images is a procedure to delineate certain required regions in the images. It is usually required for 3D visualization of certain structures, masking and regions of interest. To track the landmark points on the desired joint, segmentation of the region of interest is necessary. MRI scans can be performed in different planes, the Y-Z planar representation is called Sagittal slicing, Y-X is called Coronal and X-Z is called Transverse slicing. This project uses sagittal slices of the knee joint for segmentation, registration and tracking. Slicer 3D is good software that enables 3D segmentation and registration. This can be performed manually for all the slices of an image and contouring the boundaries or semi-automatically / fully automatically using Slicer 3D. For this project, we need to segment the right knee into 5 segments namely; Femoral cartilage, lateral tibial plateau, medial tibial plateau, lateral meniscus, and medial meniscus. Each segment in slicer is stored using different representations in which one is editable. This project requires us to use 3D representation of the segments and then perform registration for aligning them. After 3D segmentation, the MRI scans would look like this, then it needs to be registered on the required axis. Determination of Kinematics and dynamics on these MRI scans would be easier and the visualization of variable center of rotation, sliding of the tibia over the meniscus is an easy task. Tracking of the landmark point for all the slices would be the next task which can be done using the nodes and markups in slicer 3D. These nodes can be created to make landmark points on the scans. Secondary approach for this project would be segmentation using Python and OpenCV. For this, a model should be created that segments the 5 parts of the joint and then register them. All the segments would assemble to create a data set and a model that would predict the orientation and landmark points on the required knee joint.

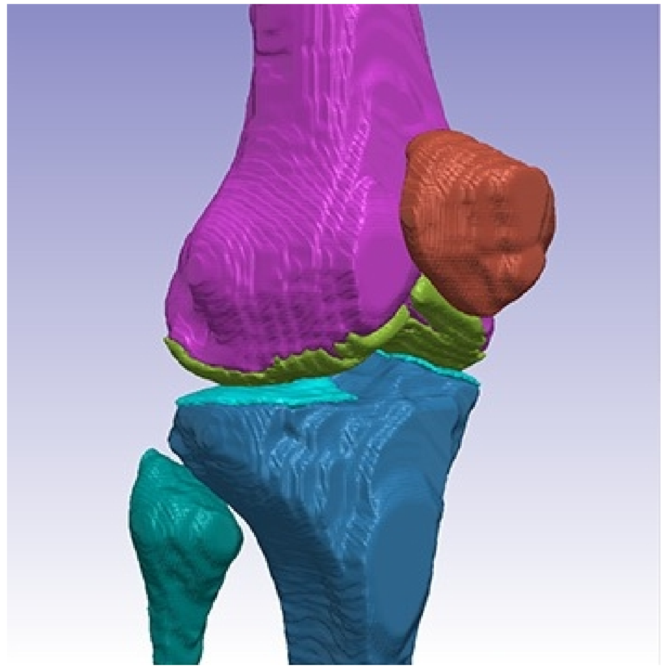

Fig. 1. Example segmentation of knee joint

B. Landmark Identification

The method we propose for carrying out automatic landmark identification is through the use of a machining learning algorithm. This algorithm will take a point cloud segment as an input and will determine the centroid of the point cloud based on point distribution. Once the centroid is identified, a search radius will be created around the centroid in which the extreme points in the proximal/distal, lateral/medial and anterior/posterior direction can be determined. This model can be trained by input data and will use linear regression to determine the radius size needed based on knee flexion. This process is further detailed in our results.

C. Principal Component Analysis

To attach a coordinate frame to each of our segments, our team proposed the use of Principal Component Analysis (PCA) to determined he first and second axes. The third axis for a 3D coordinate space could then be determined by the cross product of the first two axes. PCA works by taking large sets of data, in our case point cloud data, and using dimensional reduction to obtain axes along which the highest density of information is stored. This way the complexity of the input data can be greatly reduced while maintaining most of the useful information. The process requires input data to be standardized to eliminate bias from data with large variance. The covariance matrix of the standardized data is then computed to determine how to adjacent points relate to one another in all directions. Finally, by finding the Eigenvalues and subsequently the Eigenvectors, The principal components of the point cloud can be determined. The dependencies for this project rely on our ability to get access to the anonymous knee MRI scans that our advisors have access to. This will give us the ability to segment the knee for the femur and tibia files that we need for landmark identification and principal component analysis. The other dependency involves getting access to the MRI machine in order to conduct our own knee examinations. This data set can be used in verifying our predictive landmark identification. Our own MRI data will allow us to cross reference the landmarks and determine the overall effectiveness of our model.

V. TIMELINE

Completing our project goals in the confines of a seven week term requires careful planning of each task and objective. In constructing our timeline, our team considered the strengths and weaknesses of our team members and accounted for the diverse background we have in mechanical, and robotics engineering. Our full timeline is listed below in Table I. We tried to account for unforeseen delays and push important steps to the front to make time for iteration.

This timeline is effectively broken into two objectives, each of which our team believes could independently provide a useful end result to our project. The first objective has the end goal of being able to draw a correlation between key joint landmarks and knee kinematics based on available MRI data. The team understands that this model will need large amounts of data for statistical significance but we hope to lay the groundwork for future studies beyond a seven week term. The second objective has the end goal of being able to extend the first objective to be able to accurately and precisely predict joint kinematics simply based on MRI data input. This is an ideal case for a machine learning algorithm. However, due to the time constraint, our timeline accounts for a more direct approach to this prediction.

Task Breakdown	**Week Deadline**	**Team Member Assigned**
OBJECTIVE 1		
Aggregate Existing MRI Knee Data	Week 2 (4/1)	Team 1
Determine Gaps in Data	Week 3 (4/8)	Team 1
Generate Data to Fill Gaps	Week 3 (4/8)	All
Identify Key Knee Landmarks in MRI Data	Week 3 (4/8)	Team 2
Generate Deep Learning Algorithm for Automatic Landmark Detection	Week 4 (4/15)	All
OBJECTIVE 2		
Collect Team Member MRI Data	Week 4 (4/15)	All
Define Principle Component Axes on Femur and Tibia	Week 5 (4/22)	Team 2
Compare Automatic Landmark Detection to Ground Truth	Week 6 (4/29)	Team 2
Compile Data with Landmarks and Axes for Predictive Model	Week 6 (4/29)	All
Compile Data and Complete Report	Week 7 (5/3)	Team 1

TABLE I
ORIGINAL TIMELINE WITH TASK BREAKDOWN TEAM 1 (CALVIN AND PATRICK) TEAM 2 (VENKATESH, MATHEUS, PARTHSARTHI)

VI. RESULTS

A. MRI Data Collection and Segmentation

Our first objective dealt with collecting and creating a comprehensive data set of MRI knee images. We completed a scan of a team member's knee as our first objective towards this complete data set. We merged this data with other pre-segmented data that had been provided to us. Before our MRI data could be used in landmark identification and knee kinematic prediction, our team performed knee segmentation on the 3D scans to isolate the femur and tibia. The raw scans as well as the segmentation of two angles are shown in Figure 2. These segmentations were conducted manually in the 3D Slicer software and exported as STL files.

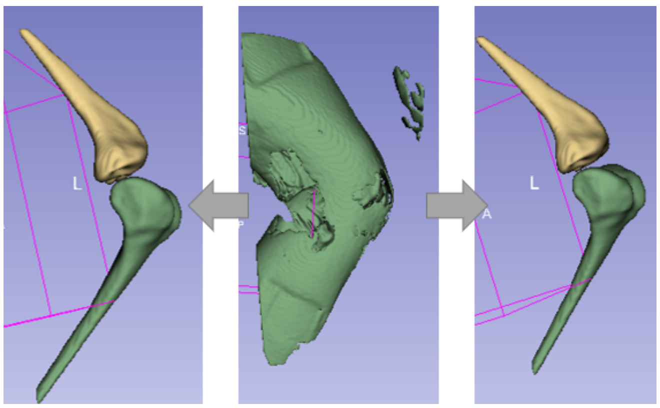

Fig. 2. Segmentation of MRI DICOM data. Example Raw DICOM input at 23 degrees (Center), 23 degree segmentation (Left), 65 degree segmentation (Right).

After segmentation, the modified images were directly imported to MATLAB as point cloud data. A major objective of our work was to be able to automatically identify key knee landmarks which could then be used to determine relative motion between the femur and tibia and would also act as known comparison points between different knees.

B. Landmark Identification

A major portion of our work this term was focused on the automatic detection of key knee landmarks. This objective would allow for future work in automatically aligning bones from different scans and patients into a single motion analysis. Using our segmented knee data base, we first developed a ground truth for our software by manually selecting landmarks based on literature and our own intuition. The landmarks we selected for the femur (See Figure 3) were the local maxima in the posterior direction as well as the distal direction. For the tibia (See Figure 4), we chose the local minima corresponding to the dips in the proximal direction as well as the local maxima in the posterior direction. Table 2 and Table 3 give the manually chosen coordinates which were used to verify the predictive model.

Degrees	x	y	z
0	78.799	22.5036	-5.3366
23	-27.6459	-32.9813	-24.4655
52	-48.995	92.5836	2.7104
84	-100.496	91.6010	-6.5932

TABLE II
ACTUAL VALUES OF LATERAL INTERCONDYLAR TUBERCLE FOR TIBIA LANDMARK

Degrees	x	y	z
0	68.4515	56.2426	-7.1754
23	-17.1814	-43.3911	-24.4469
52	-52.0418	124.1997	0.8675
84	-110.945	126.1899	-10.3889

TABLE III
ACTUAL VALUES OF LATERAL DISTAL POINT FOR FEMUR LANDMARK

Having identified and stored the coordinates for the key landmarks on all scan angles, We developed a machine learning algorithm to automatically identify these points. The point cloud data was first imported into python. The process then used a k-d tree to partition the point cloud into a k dimensional space. For our analysis, we determined k = 20000 was sufficient for accuracy while minimizing processing requirements. The center of mass of each segment was then determined by comparing the number of points in each dimension and finding the point most center to the cloud. Using the centroid as a starting point, a circle of arbitrary radius was drawn that encompassed the bone. This radius is a tunable parameter for our machine learning algorithm. For our predictive model we mainly focused on 2 key points one on each tibia and femur. We chose **Lateral Distal Point** for the Femur whereas **Lateral Intercondylar Tubercle** for the Tibia (See Fig. 5.). We found the 2 landmarks by traversing all the points of the k-d tree which were inside that finely tuned circle for 4 angles of our MRI data and predicted these landmarks for the fifth angle.

The four angles we used for sampling were 0, 23, 52, and 84 degrees and kept 65 degrees to test the accuracy of our model. We use Linear Regression to predict the radius which would encompass the landmarks for the 65 degree angle.

The points we got after k-d traversal for the first 4 points were Table IV for Femur and Table V for Tibia. Our ground truth by manual labeling can be seen in

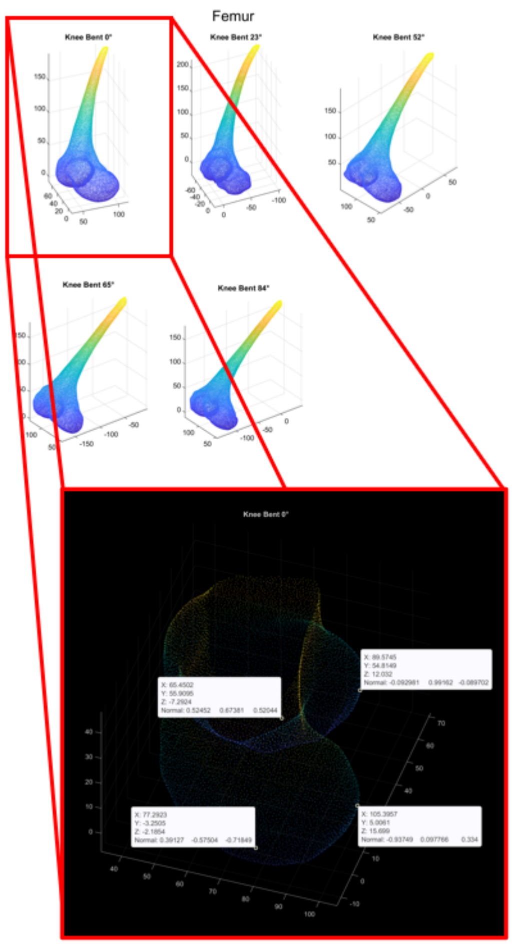

Fig. 3. Example Femur manual landmark detection as ground truth based on literature. Point cloud files for all knee angles were imported (above). Manual landmarks were identified and coordinates were stored (Below)

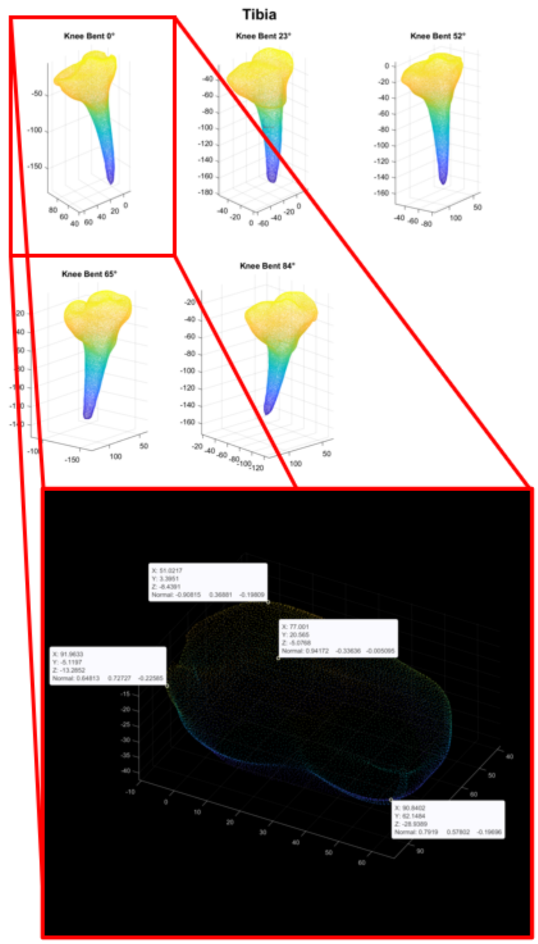

Fig. 4. Example tibia manual landmark detection as ground truth based on literature. Point cloud files for all knee angles were imported (above). Manual landmarks were identified and coordinates were stored (Below)

Degrees	x	y	z
0	75.614	42.384	-1.9121
23	-27.0717	-44.605	-23.624
52	-45.325	110.351	4.1775
84	-105.127	118.499	-9.1135

TABLE IV

PREDICTED VALUES OF **Lateral Distal Point** WITH MANUALLY TUNED RADIUS

Degrees	x	y	z
0	68.6120	18.5190	-4.5048
23	-26.3936	-3.6255	-25.341
52	-56.7131	79.859	6.2178
84	-86.9617	66.564	-4.3424

TABLE V

PREDICTED VALUES OF **Lateral Intercondylar Tubercle** WITH MANUALLY TUNED RADIUS

Tables II and III. To compare the points, we used an RMSE model detailed below. The Linear Regression fit for both femur and tibia can be seen in Fig 6 and Fig 7.

As we only had 5 data points so our model is quite sensitive. We can see that outliers in the Tibia caused difficulty in generalizing the optimal radius for 65 degrees. For future work we can collect more data to make our model robust to such outliers.

Final predictive plots can be seen in Fig 8 for Femur and Fig 9 for Tibia at 65 degree orientation. The prediction for **Lateral Distal Point** is quite accurate. Our model struggles ,as can be with, **Lateral Intercondylar Tubercle** due to low data points available for sampling. Our final predicted points can be seen in Table IV.

To verify the accuracy of our predictive model to

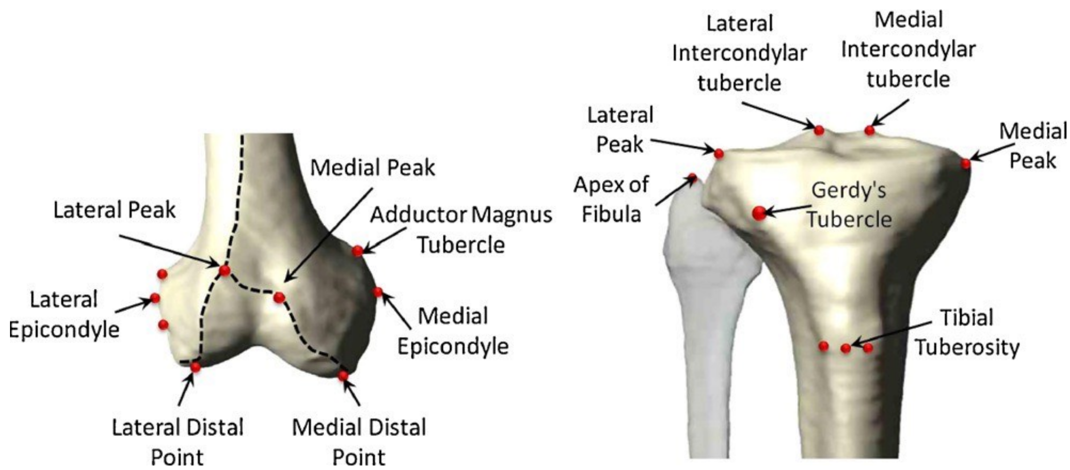

Fig. 5. Key landmark locations obtained from literature for Femur(Left) and Tibia(Right)

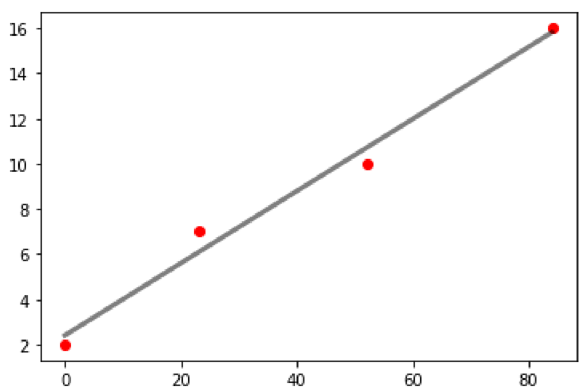

Fig. 6. Linear Regression fit for the 4 points for Femur. x-axis represents knee angle in degrees and y-axis is corresponding search radius in mm.

65 Degrees predictions	x	y	z
Lateral Distal Point	**-119.8001**	**102.3511**	**84.2527**
Lateral Intercondylar Tubercle	**-125.039**	**61.1229**	**-3.1643**

TABLE VI

PREDICTED VALUES FOR 65 DEGREE ANGLE

the manually obtained ground truth, we calculated the RMS Error for all the values in Table IV and Table V and determined the average magnitude of error. We used the standard RMSE equation shown below.

$$RMSE = \sqrt{\frac{1}{n}\Sigma_{i=1}^{n}(Predicted_i - Actual_i)^2}$$

Using this equation and the comparing the value from Table I and Table II to our predicted values we found the RMSE to be around 11mm for the Tibia and 7mm

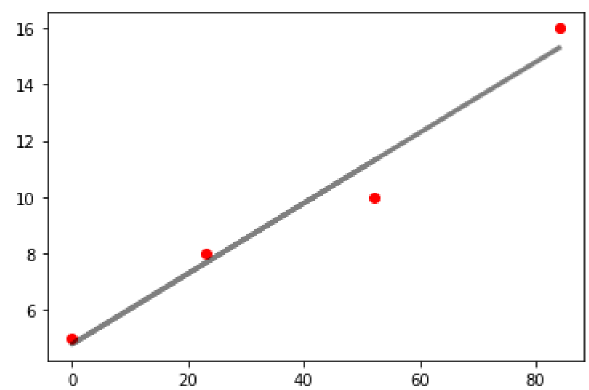

Fig. 7. Linear Regression fit for the 4 points for Tibia. x-axis represents knee angle in degrees and y-axis is corresponding search radius in mm.

for the Femur as shown in Table VIII. We had a significant outlier in our 65 degree femur prediction so we chose to display the error with and without this outlier.

RMSE	x	y	z	Ave
With 65 Degrees	**8.44**	**24.72**	**2.13**	**11.77**
Without 65 Degrees	**9.32**	**20.57**	**2.17**	**10.69**

TABLE VII

TIBIA RMSE FOR PREDICTED AND ACTUAL LANDMARK COORDINATES

C. Principle Component Analysis and Axis Determination

The last key portion of our work dealt with defining the principle axes of each bone segment to be used in

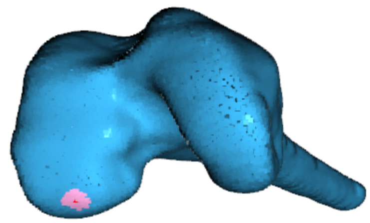

Fig. 8. Predicted **Lateral Distal Point** for 65 degrees

Fig. 9. Predicted **Lateral Intercondylar Tubercle** for 65 degrees

RMSE	x	y	z	Ave
With 65 Degrees	**13.09**	**12.70**	**39.51**	**21.7**
Without 65 Degrees	**7.55**	**10.54**	**3.20**	**7.09**

TABLE VIII

FEMUR RMSE FOR PREDICTED AND ACTUAL LANDMARK COORDINATES

conjunction with the identified landmarks for kinematic analysis. Using Principal Component Analysis (PCA) which was detailed in the project methodology, our team was able to effectively define the first and second principal components of each knee segment simply based on cloud data. Using the first two components, we derived the third axes using cross-product and attached the newly constructed coordinate frame to each segment. The results for a representative tibia and femur are shown in Figure 10.

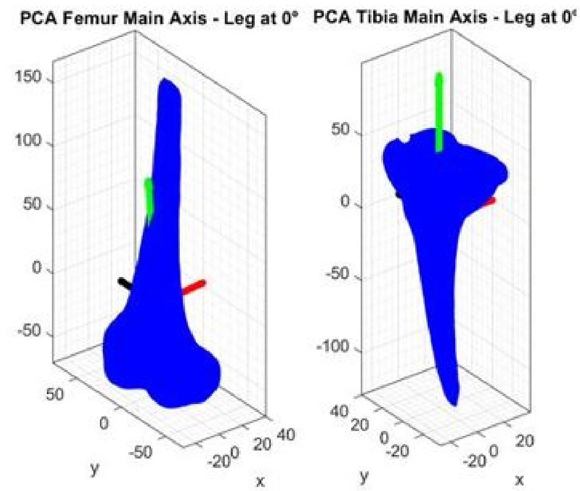

Fig. 10. Principal axis coordinate frame for a femur and tibia pair at 0 degrees

VII. DISCUSSION

From our results, our expected goals were to segment and analyze the MRI data, automatically identify the key landmarks, and develop a coordinate frame based on principal axes. Due to time constraints, the group was not able to accomplish our reach goal of using our framework to perform kinematic analysis. Our segmentation and landmark identification results were promise for further pursuit of a fully automatic kinematic model of a patient's knee simply based on an MRI scan. Additionally, the team was able to successfully create a coordinate framework for the tibia and femur segments which allows for easy implementation of kinematic analysis in the future. Building a groundwork for this functionality was the main purpose of our project and was well achieved given our results. Some limitations of this work included the relatively small data set that we were working with throughout the term. To generate statistical significance, more data sets would need to be analyzed.Another limitation which is an opportunity for future work is that, although are landmarks were accurately identified, their use in axis definition and kinematic modeling was not verified. Future investigation is needed to better determine if the selected landmarks are adequate for our needs.

VIII. CONCLUSION AND FUTURE WORK

Our projected was aimed at developing a framework for knee kinematic comparison based on MRI data input. Given the confines of our term, we broke down this objective into achievable tasks that would lay the groundwork for the end goal. We collected and compiled a comprehensive MRI data set containing segmented STL files for both femur and tibia at various angles of flexion. To automatically identify key landmarks, we developed an algorithm which used machine learning to automatically generate local maxima and minima using point cloud data. We then compared the point to the ground truth landmarks derived manually from the STL files and found our algorithm to be within 7-11mm of the actual points on average. Our PCA analysis was able to robustly define a coordinate frame on each segment with no outliers in our data set. For future work, a more robust mechanism for automatic landmark detection should be trained by using a larger data set in our algorithm. PCA must be verified with more data and compared to a ground truth. Finally, the knee landmark locations in the aligned coordinate frames can be recorded and compared as the segments are brought through their range of motion to build a kinematic data set.

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