

Unsupervised Machine Learning Driven Dynamic Alignment Classification Under Controlled Load In Navigated Total Knee Arthroplasty

Prudhvi Tej Chinimilli, Laurent Angibaud¹, Amaury Jung, James Irvin Huddleston

¹Advanced Surgical Technologies

INTRODUCTION:

Traditional alignment classification for total knee arthroplasty (TKA) as neutral, varus, and valgus oversimplifies the complexity of individual anatomy. Personalized alignment techniques, such as kinematic and functional alignment, have led to more nuanced radiological classifications, yet these static, weight bearing radiographs fail to capture the dynamic nature of hip-knee-ankle (HKA) alignment during gait. This study introduces a novel intraoperative method to measure dynamic HKA (dHKA) using an intra-articular device coupled with a computer assisted surgery (CAS) system. The device applies a quasi-constant distraction force throughout the knee's range of motion, stabilizing the joint and facilitating neutral alignment. An unsupervised machine learning (ML) model is applied to develop a classification based on patient-specific dHKA profiles. The objectives of this study are twofold: 1) to perform unsupervised clustering of dHKA measurements obtained before (pre-cut) and after (post-cut) the femoral cut, within a tibia-first surgical workflow and 2) to quantify how often post-cut alignment clusters match the patient's pre-cut alignment clusters, stratified by surgeon.

METHODS:

This study analyzed tibia-first TKA cases performed by 11 surgeons. Cases with flexion contracture were excluded, resulting in a final dataset of 1890 cases. The tibia-first surgical workflow is illustrated in Figure 1. Before the femoral cut (pre-cut stage), an intra-articular device is placed between the tibia cut and the femur to apply a consistent distraction force across the knee compartments. Medial and lateral gaps, along with the pre-cut dHKA are recorded (Figure 1c). After the femoral cut (post-cut stage), a trial component is placed, and the intra-articular device is reinserted. The knee is flexed, and the trial component's position relative to the tibia cut is captured by CAS to provide final gap measurements and post-cut dHKA (Figure 1e). For each case, varus and valgus (VV) angles are available at 12 distinct flexion angles (0° to 120°) for both the pre-cut and post-cut stages. The two-dimensional dHKA data (VV and flexion) is transformed into a 12-dimensional feature space, with each dimension representing the VV angle at a specific flexion angle. An unsupervised ML model (K-means) was trained on the transformed pre-cut dHKA data to identify dynamic alignment profiles. Clustering evaluation metrics were used to determine the optimal number of clusters and feature space combination. The trained pre-cut model was then applied to post-cut data to assign post-cut cluster labels, enabling direct comparison using consistent cluster boundaries.

RESULTS:

Clustering evaluation identified 4 distinct dHKA clusters and an optimal 8-dimensional feature space (VV angles at 10°, 20°, 30°, 45°, 60°, 75°, 90°, 105° of flexion). Figure 2 presents the clustering results, including three-dimensional scatter plots, cluster centroids, and dHKA trajectories for both pre-cut (Figure 2a) and post-cut data (Figure 2b). The clusters were clearly distinguishable, with distinct centroid trajectories illustrating the evolution of alignment across the flexion arc. Pre-cut/post-cut cluster distributions were: cluster 1 (15.3%/14.2%), cluster 2 (35.9%/30.1%), cluster 3 (34.2%/35.6%), and cluster 4 (14.5%/20.2%). Based on cluster centroids and dHKA profiles, cluster 1 was characterized as valgus and neutral, cluster 2 as neutral, cluster 3 as low to moderate varus, and cluster 4 as moderate to high varus. The Sankey diagram in Figure 3 illustrates transitions between pre-cut and post-cut clusters. Most transitions occurred between adjacent clusters (e.g., 2 to 3, 3 to 4), while extreme transitions (e.g., cluster 1 to 4) were almost zero. Overall, 1312 cases (69.4%) of the cases retained their original cluster post-cut, with surgeon-specific match rates ranging from 61% to 88% (Table 1), indicating variability in how closely surgeons preserve a patient's pre-cut alignment profile.

DISCUSSION AND CONCLUSION:

By capturing patient-specific alignment profiles throughout the range of motion, this approach advances beyond current static classification systems to reflect dynamic joint behavior under functional conditions. This study demonstrates the first application of unsupervised ML to classify intraoperative dHKA profiles obtained using a force-controlled intra-articular device in combination with CAS. This intraoperative method enables real-time feedback and offers a foundation for an automated dynamic alignment classification tool to support personalized decision-making in TKA.

Figure 1: Overview of the tibia-first TKA surgical workflow with intra-articular device and CAS

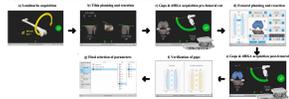


Figure 2: dHKA clustering results (pre-cut (top) and post-cut (bottom))

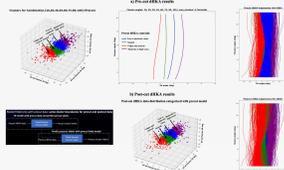


Figure 3: Sankey diagram showing pre-cut to post-cut cluster transitions (top) and cluster transition matrix (bottom)



Table 1: Cluster match rates for 11 surgeons. N: total number of cases, M: number of cases with cluster matches

Surgeon	Cluster match %
Surgeon 1 (N=100)	88%
Surgeon 2 (N=120)	85%
Surgeon 3 (N=150)	82%
Surgeon 4 (N=180)	78%
Surgeon 5 (N=200)	75%
Surgeon 6 (N=220)	72%
Surgeon 7 (N=250)	70%
Surgeon 8 (N=280)	68%
Surgeon 9 (N=300)	65%
Surgeon 10 (N=320)	62%
Surgeon 11 (N=350)	61%