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

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Disclosures: P. Chinimilli: 3A; Exactech. 4; Exactech. L.D. Angibaud: 3A; Exactech. 4; Exactech. 9; Personalized Arthroplasty Society. A. Jung: 3A; Blue-Ortho. 4; Exactech. J. Huddleston: 3B; Exactech. 9; American Association of Hip and Knee Surgeons.

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[1-2]. This study introduces a novel intraoperative method to measure dynamic HKA (dHKA) using an intra-articular device coupled with a computer assisted orthopaedic surgery (CAOS) 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. This is crucial for improving patient satisfaction and functional outcomes after total knee arthroplasty (TKA). Traditionally, surgeons aimed to restore neutral alignment during surgery.

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 CAOS system 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 (Figure 2a).

RESULTS SECTION: Clustering evaluation identified 4 distinct dHKA clusters (Figure 2b) 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 2c) and post-cut data (Figure 2d). 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 3a 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% (Figure 3b), indicating variability in how closely surgeons preserve a patient's pre-cut alignment profile.

DISCUSSION: 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 CAOS system. 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.

SIGNIFICANCE/CLINICAL RELEVANCE: The significance of this work lies in establishing a dynamic, machine learning based intraoperative alignment classification that captures patient-specific joint behavior.

REFERENCES:

1. Indelli PF et al. The epidemic of alignment classifications in total knee arthroplasty forgives the kinematic of the human knee. Journal of Experimental Orthopaedics. 2024; 11(4): e70052
2. Clément J et al. Hip-Knee-Ankle (HKA) angle modification during gait in healthy subjects. Gait & Posture. 2019; 72: 62-68

IMAGES AND TABLES:

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

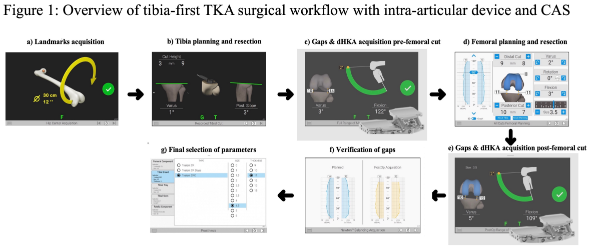


Figure 2: dHKA clustering results

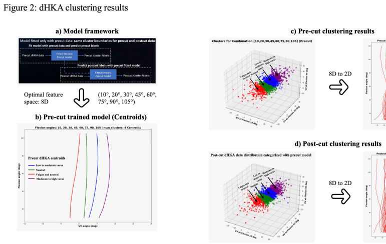
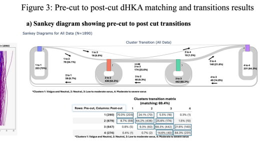


Figure 3: Pre-cut to post-cut dHKA matching and transitions results



Rows: Pre-cut, Columns: Post-cut	1	2	3	4
1 (290)	70.0% (203)	24.1% (70)	5.5% (16)	0.3% (1)
2 (679)	8.7% (59)	64.2% (436)	25.6% (174)	1.5% (10)
3 (647)	0.8% (5)	9.3% (60)	68.3% (442)	21.6% (140)
4 (274)	0.4% (1)	0.7% (2)	14.6% (40)	84.3% (231)

*Clusters 1: Valgus and Neutral, 2: Neutral, 3: Low to moderate varus, 4: Moderate to severe varus

b) Cluster match rates for 11 surgeons, N: total number of cases, M: number of cases with cluster matches

Surgeon	Cluster match %
Surgeon 1 (N=266)	73.7% (M=196)
Surgeon 2 (N=126)	69.8% (M=88)
Surgeon 3 (N=527)	72.1% (M=380)
Surgeon 4 (N=70)	68.6% (M=48)
Surgeon 5 (N=444)	61% (M=271)
Surgeon 6 (N=32)	68.8% (M=22)
Surgeon 7 (N=56)	66.1% (M=37)
Surgeon 8 (N=58)	72.4% (M=42)
Surgeon 9 (N=156)	69.9% (M=109)
Surgeon 10 (N=113)	72.6% (M=82)
Surgeon 11 (N=42)	88.1% (M=37)