Dynamic Knee Deformity Classification: Unsupervised Machine Learning Clustering of TKA Cases with a Computer Assisted Surgery System

Prudhvi Tej Chinimilli[1], Laurent Angibaud[1], Amaury Jung[2], François Boux De Casson[2], James Irvin Huddleston[3]
[1]Exactech, [2]Blue-Ortho, [3]Stanford Medicine

INTRODUCTION:

Restoring normal knee kinematics is crucial for improving patient satisfaction and functional outcomes after total knee arthroplasty (TKA). Traditionally, surgeons aimed to restore neutral alignment during surgery. However, studies[1-2] have shown alignment to be dynamic, varying depending on the limb, degree of weight-bearing, and between patients. Additionally, arthritic knees exhibit distinct deformity patterns in the coronal plane as they move from extension to flexion. Current methods[3] for assessing alignment and deformity are inadequate as they only describe the parameters at a static moment. Therefore, this paper aims to propose a novel automated dynamic knee deformity classification model that categorizes patient deformity utilizing varus and valgus (V&V) angles throughout the full flexion arc, captured with a computer-assisted surgery (CAS) system.

METHODS:

A retrospective review was conducted using a proprietary cloud-based database that archives technical logs from an instrumented CAS system. A total of 1336 cases by 11 surgeons with atleast 20 cases each were considered without any exclusions. For each case, preoperative kinematics were captured prior to performing bone cuts, and example of the preoperative kinematics screen is shown in Figure 1. For each case, V&V angles were recorded for full flexion arc (0° to 120°), providing data in two dimensions: flexion and V&V. For data preparation, cases were first categorized as either flexion contracture (FC) cases or non-flexion contracture (NFC) cases based on 10° lowest preoperative flexion angle threshold. Of the total 1336 cases, 1221 were classified as NFC and 115 as FC. Next, the two-dimensional input data (flexion and V&V angles) for both FC and NFC were transformed into an M-dimensional features space, where each dimension is represented as the V&V angle at a specific flexion angle. Since, V&V angles were captured at 9 distinct flexion angles, M equals 9. This resulted in the training dataset size of 1221 x 9 for NFC cases, and 115 x 9 for FC cases. An unsupervised clustering model, k-means, was applied on the training data to determine optimal number of clusters i.e., deformity categories. The elbow technique was used to choose the optimal number of clusters and feature space by calculating the Within Cluster Sum of Squares (WCSS) metric for each combination.

RESULTS:

k-means clustering evaluation identified 5 clusters and 8 features — V&V angles at (10°, 20°, 30°, 45°, 60°, 75°, 90°, 105°) as the optimal combination. Figure 2 displays NFC clustering results with five colors representing data points of each cluster. Since visualizing an 8-dimensional space is impractical, three-dimensional features with V&V angles at 10°, 45°, and 90° flexion are shown. The right side of Figure 2 displays centroids showing mean V&V angles for 8 flexion angles for each cluster. The five clusters are named as neutral, valgus, low varus, moderate varus, and high varus. The clusters are clearly distinguishable, with centroid curves indicating distinct V&V trajectories throughout the flexion arc. The centroid curves illustrate how mean deformity evolves from extension to flexion. For instance, valgus cluster centroid curve shows that the valgus angle decreases from severe valgus in extension to low valgus in flexion. Figure 3 shows the distribution of cases per surgeon in percentages, using heat map visualization. Notably, there are clear differences in the cases distribution among surgeons. For instance, surgeon 11 has more cases in the high varus cluster, whereas surgeon 2 has more cases in the neutral cluster.

DISCUSSION AND CONCLUSION:

To the best of authors knowledge, this study is the first to apply an unsupervised machine learning clustering model to categorize patient deformity based on dynamic preoperative kinematics data captured throughout the full flexion arc. This model will help surgeons better assess knee deformities by understanding the distinct patterns across the full flexion arc, rather than relying on a single static measurement in extension or at 90 degrees of flexion. Collateral soft tissue release based on deformity in extension may be underlying cases of flexion instability[1], an issue that can be mitigated by using dynamic knee deformity classification models. The significance of this work lies in developing robust automatic assessment of dynamic knee deformity classification that may enhance the decision-making process for surgeons performing TKA.

References:

1. Deep K et al. Dynamic knee behaviour: does the deformity change as it is flexed – an assessment and classification with computer navigation. Knee Surgery, Sports Traumatology, Arthroscopy. 2016; 24: 3575-3583
2. Larrainzar-Garijo R et al. Dynamic alignment analysis in the osteoarthritic knee using computer navigation. The Journal of Knee Surgery. 2017; 30(09): 909-915

3. MacDessi SJ et al. The arithmetic HKA (aHKA) predicts the constitutional alignment of the arthritic knee compared to the normal contralateral knee: a matched-pairs radiographic study. Bone & Joint Open. 2020. 1(7); 339-345

Figure 2: NFC clustering results trained on 1221 cases from 11 surgeons. Number of clusters: 5 (neutral, valgus, low varus, moderate varus, and high varus)

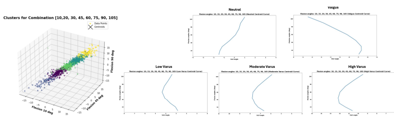

Figure 3: Heatmap displaying cases distribution for 11 surgeons corresponding to 5 clusters

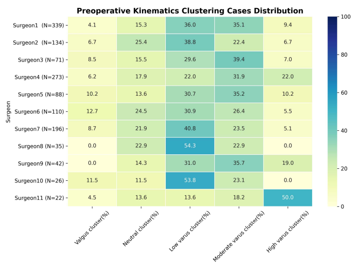

Figure 1: Preoperative kinematics screen displaying V&V angles captured at various angles of flexion