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| Slide 1 |  | This presentation demonstrates a semi-automated method for tracking tibiofemoral motion in dynamic MRI  Let’s begin with the motivation behind this work. |
| Slide 2 |  | Accurate osteokinematic analyses are essential for diagnosing joint dysfunctions, designing implants, and monitoring rehabilitation. While dynamic MRI provides great insight into joint motion, it is limited by time-consuming manual segmentations, reliance on static reference scans, and complex registration pipelines. Our work attempts to address these limitations |
| Slide 3 |  | Osteokinematics refers to bone motion around a joint. In the knee, altered kinematics can both lead to and result from joint pathologies. Capturing this motion dynamically is difficult, and even when successful, extracting reliable kinematic parameters from sequences like CINE MRI remains technically challenging |
| Slide 4 |  | Our goal was to develop a semi-automated bone tracking pipeline to extract kinematic parameters from sagittal-plane CINE MRI. We aimed to reduce processing time, eliminate the need for high-resolution reference scans, and improve consistency compared to manual segmentation. |
| Slide 5 |  | Here you see our custom-built MRI-compatible motion device. It was specifically designed to allow controlled, repeatable flexion and extension of the knee inside the scanner. On the right, we show a subject using the device during calibration outside the bore |
| Slide 6 |  | The motion is cyclic and guided by a metronome, producing repeatable knee flexion-extension cycles.  An integrated optical sensor records the knee angle in real time. This angular data is later used to retrospectively sort the k-space data into discrete motion frames, effectively reconstructing a dynamic CINE sequence. |
| Slide 7 |  | We acquired dynamic MRI data from five healthy volunteers, performing controlled knee flexion-extension at 7.5 cycles per minute, guided by a metronome.  Scans were done on a 3T system using a 2D radial golden-angle FLASH sequence. The optical position sensor captured real-time knee angles, which we used to retrospectively sort the acquired k-space data into 2-degree angle intervals.  Here, you see both the individual frames and the reconstructed motion loop. Each frame corresponds to a specific knee angle. This CINE series forms the basis for our subsequent tracking analysis |
| Slide 8 |  | The tracking approach consists of four key steps: edge detection, component labeling, reference point selection, and frame-to-frame transformation optimization. This sequence allows us to estimate bone motion across the dynamic frames using only the segmentation done for the first frame |
| Slide 9 |  | We assume rigid body motion of the femur and tibia in the sagittal plane, modeled with three parameters: two translations and one in-plane rotation.  For each frame, we estimate a rigid transformation that maps the reference contour from the first frame onto the detected bone edges by minimizing the point-to-edge distance using nonlinear least squares |
| Slide 10 |  | Manual segmentation is done only once, in the first frame. Using the frame-to-frame transformations, we propagate this segmentation across all frames.  We compute the geometric centroids of the femur and tibia, shown as cross symbols on the image, and track the relative displacement of the tibia with respect to the femur throughout the motion cycle.  We also validate the method by comparing it against manual segmentation for every frame |
| Slide 11 |  | The method successfully tracked both bones across the entire motion cycle.  The mean boundary alignment error was just 0.40 millimeters. Processing time per dataset dropped from around 15 minutes manually to under 5 minutes with our pipeline.  Horizontal displacement ranged from 8 to 28 mm, while vertical displacement remained stable at around 57 mm |
| Slide 12 |  | Here you can see how the segmentation is propagated over time. The coloured overlays show the tibia and femur contours as they move together through the motion cycle |
| Slide 13 |  | We compared manual and semi-automated methods for both horizontal and vertical displacement.  While both approaches captured the same motion patterns, the semi-automated method yielded lower standard deviations, as can be seen in the graph. |
| Slide 14 |  | These results show that our semi-automated method not only reproduces the expected motion trends but does so with lower variability than manual segmentation.  In both directions, the standard deviations were smaller, indicating more consistent measurements across subjects. |
| Slide 15 |  | To conclude, this technique enables direct analysis of dynamic MRI without requiring static reference scans.  It leverages full bone contours instead of landmarks, streamlining the workflow and improving reproducibility.  The method is well-suited for larger studies or clinical applications, especially in conditions affecting knee mechanics. |
| Slide 16 |  | We gratefully acknowledge funding support from the German Research Foundation. |