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1 Introduction

The study of relative motion between the femur and tibia during knee joint movement is crucial for understanding normal knee function and identifying pathological conditions [1]. Accurate assessment of knee movement patterns can provide valuable insights for the diagnosis and treatment of various knee disorders, including ligament injuries and osteoarthritis [2–4]. For instance, studies have shown that the kinematics of anterior cruciate ligament-deficient knees are altered under various conditions. During walking, ACL-deficient knees demonstrated changes in tibial rotation patterns [5]. In a controlled knee extension exercise, these knees exhibited increased anterior tibial translation compared to healthy knees [6].

These alterations in knee motion observed in ACL-deficient knees exemplify how ligament injuries can lead to increased joint laxity and instability [7]. Such instability can result in higher tissue strains and abnormal loading patterns throughout the joint [8]. Over time, these biomechanical changes may contribute to the development and progression of osteoarthritis, one of the most common joint disorders affecting a significant portion of the global population [9].

Dynamic MRI has emerged as a promising tool for studying in vivo knee motion, offering insights into both normal and pathological knee function under realistic conditions. While not yet widely adopted as a standard approach, several studies have demonstrated its utility in capturing knee movement. These studies have employed various dynamic imaging techniques, including real-time MRI [10,11], CINE MRI [12,13], and cine phase contrast MRI [14,15], and methods incorporating specialized devices for controlled loading conditions [16,17] each offering unique capabilities for capturing in vivo knee motion.

In these dynamic MRI studies of knee motion, researchers have employed various methods to extract kinematic parameters. Some studies used high-resolution static MRI scans to create detailed 3D models of the bones, which were then registered to lower-resolution dynamic MRI frames [10,16]. Alternatively, some studies have employed landmark-based tracking methods, such as using a semi-automatic tracking algorithm where bony landmarks are manually identified in the first dynamic frame and then tracked across subsequent frames using normalized cross-correlation [11]. Others have used motion-triggered imaging to compare bone position measurements between static and dynamic conditions [13].

In this work, we present a semi-automated method for tracking bone motion in 2D sagittal CINE MRI sequences acquired during controlled knee flexion-extension using a custom MRI-compatible loading device. Our approach uses edge detection followed by frame-to-frame transformation optimization to automatically propagate initial bone segmentations throughout the motion cycle. Unlike previous approaches, our technique operates directly on the dynamic frames without requiring additional static scans, potentially streamlining the overall analysis process. The primary objective was to develop this bone tracking method with minimal manual input requirement. To validate our approach, we performed manual segmentation across all frames and compared the results. We then analyzed relative bone positions using centroid-based distance measurements throughout the motion cycle, demonstrating that our semi-automated method achieves improved measurement precision while significantly reducing processing time compared to manual approaches

2. Material and Methods

2.1 Image Acquisition and Reconstruction

Five healthy volunteers (three males and two females, age 24-39 years, body mass 55-90 kg) participated in this study. Dynamic MRI scans were acquired for the left leg of each participant using a 3 T clinical whole-body MRI scanner (MAGNETOM Prisma, Siemens Healthineers).

A custom MRI-safe knee motion and loading device [18] was used to guide knee motion and ensure consistent, planar movement during flexion-extension cycles. Participants were positioned supine in the scanner with their thigh secured on a wedge positioner using a strap. The lower leg was secured to an ankle support positioned just proximal to the malleolus using Velcro straps to attach the leg to the device arm. Additional straps were applied around the thigh to minimize unwanted lateral movement. The knee joint center was carefully aligned with the device's axis of rotation, allowing only flexion and extension movements in the sagittal plane. Two flexible 16-channel multifunctional coils (Variety, Noras MRI products GmbH) were used to ensure comprehensive coverage of the knee region. One coil was positioned beneath the knee, with the posterior aspect of the knee resting directly on it. The second coil was wrapped around the anterior aspect of the knee, covering the proximal tibia.

During the scan, participants performed controlled extension-flexion cycles of the knee joint to the beat of a metronome (60 beats per minute). Each knee extension-flexion movement cycle was guided by eight metronome beats, with the knee fully flexed at the first beat, fully extended by the fourth beat and fully flexed again by the eighth beat, resulting in 7.5 cycles per minute. The knee range of motion achieved by the participants varied between 30 and 46 degrees. The total scan duration was 160 seconds, allowing for the acquisition of approximately 20 full knee extension-flexion cycles.

MRI data were acquired using a 2D radial golden-angle gradient echo FLASH sequence [19,20] with the following parameters: echo time of 2.51 ms, flip angle of 8 degrees, field of view of [192×192×3] mm, matrix size of [176×176×1], voxel size of [1.09×1.09×1] mm, and repetition time of 5.8 ms. During reach repetition, 276 spokes were acquired, with each spoke consisting of 352 data points. A total of 100 k-space repetitions were acquired during the scan session.

This acquisition method enables CINE MRI, which continuously acquires k-space data throughout the knee motion cycle. By retrospectively sorting the k-space data into discrete knee angle intervals, a series of images or frames representing the knee at different flexion-extension positions is created, effectively producing a ‘cinema’ of the joint motion.

Image reconstruction was done using an optical fiber position sensor (MR338-Y10C10, Micronor, Camarillo, CA, USA) integrated into the knee device. This optical sensor measured the knee rotation angle with a precision of 0.025° using optical signals. The optical signals were first converted to electrical signals by a controller (MR330, Micronor), which were then sampled simultaneously with the MRI scanner's trigger signal using a USB-based data acquisition module (RedLab 1208FS Meihaus Electronic GmbH). By synchronizing the knee rotation angles with the start of each k-space repetition, the radial golden-angle k-space data were then sorted into two degree windows of knee rotation [21]. This process was repeated for the entire range of motion, ensuring comprehensive coverage of the knee’s range of motion. Image reconstruction was performed using the RIESLING (Radial Interstices Enable Speedy Low-volume imagING) toolbox [22]. This open-source software package is specifically designed for reconstructing non-Cartesian MRI data, employing advanced algorithms to efficiently handle the radially sampled k-space data. Specifically, the “Alternating Direction Method of Multipliers” algorithm within RIESLING was used, with “Total Generalized Variation” regularization. A regularization strength of 0.05 was used, which was empirically determined to balance noise suppression and edge sharpness. Image reconstruction was performed separately for knee extension (upward leg movement) and knee flexion (downward leg movement) to account for biomechanical differences.

The final reconstructed 2D-CINE datasets had a varying number of frames based on each participant's achievable range of motion. Participants with a larger range of motion had more frames available for reconstruction as compared to participants with lower range of motion. **Figure 1** shows a series of reconstructed frames from a single dataset, showcasing the progression of knee motion from a flexed position, to extended position, back to flexed position, which are used subsequently as the input data for bone segmentation and tracking.

2.2 Semi-Automated Bone Tracking

For semi-automated tracking of the tibia and femur, the following tracking algorithm was implemented in Python (v.3.11.5):

(I) Edge Detection: The Canny edge detection algorithm was applied to each frame to identify the boundaries of the tibia and femur [23]. Parameters such as gradient thresholds and Gaussian blur strength were optimized manually to isolate the bone edges. This step resulted in binary images highlighting the detected edges, including the interior cortical bone boundaries.

(II) Edge Labeling: Connected-component labeling [24] was performed on the binary edge images to isolate specific structural features and distinguish the desired interior cortical bone edges from other detected edges. The labeling algorithm groups adjacent pixels into distinct regions or "components". The algorithm’s connectivity settings were adjusted to define how pixels are considered connected (e.g., diagonally adjacent pixels were considered to be part of the same component). These settings were carefully tuned to ensure that each bone's interior edge was consistently identified as a single, continuous component across the entire image stack. In steps I and II, the edge detection and labeling parameters were optimized once for the given image contrast and resolution, and then applied consistently across all datasets and frames.

(III) Reference Point Extraction: A set of reference points was established along the labeled edges of the tibia and femur in the initial frame (fully flexed position). The process began by identifying the most distal point of each bone and then sorting the edge points using a greedy nearest neighbor algorithm [25]. The sorted points were then downsampled to 80 equidistant points using cubic spline interpolation [26]. By establishing these reference points in the initial frame, a template of equidistant points along the bone edges was created that could be transformed to match the bone positions in subsequent frames, facilitating the tracking of bone movement throughout the motion sequence.

(IV) Transformation Computation: Frame to frame transformations were computed to align the equidistant reference points of the bone edges. This process assumed rigid body motion, considering only translations in the sagittal plane and rotations about the transverse axis perpendicular to the sagittal plane. As such, the transformation was described using three parameters: two translations in the inferior-superior and anterior-posterior directions and one rotation in the axis perpendicular to the sagittal plane. **Figure 2** demonstrates this process, showing how reference points established in the initial frame (orange dots) can be transformed to align with the bone edge at any point during the motion cycle through the computation of optimal transformation parameters.

To compute the optimal set of these three parameters, a cost function was defined. This function quantifies the total non-overlapping distance between the target frame and transformed frame, with a perfect alignment resulting in an output of 0. The goal was to find the combination of transformation parameters that minimizes the output of this cost function. The minimization of this cost function effectively identifies the optimal way to track the bone edges between consecutive frames.

The Nelder-Mead method was used to minimize the cost function and obtain the frame-to-frame transformation parameters [27]. To guide the search, constraints were applied based on a priori knowledge of the motion characteristics. For instance, the rotation was restricted to the expected range of frame-to-frame angle increments used during reconstruction, while the translations were limited to relatively small values to account for the continuous nature of the motion.

Once the parameters were obtained for all the frames, any manual segmentation of the bones drawn in the first frame, could be automatically transformed to all other frames.

A schematic overview of the tracking algorithm is shown in **Figure 3**.

2.3 Manual Segmentation and Parameter Estimation

To compare the accuracy and reliability of the proposed bone tracking algorithm, segmentation was performed manually for all frames and datasets using the Napari (v.4.16) image processing software [28]. For this purpose, the bone segmentation obtained in the first frame was manually aligned (translated and rotated) to match the new bone positions in subsequent frames.

For both manual and semi-automated segmentations, relative bone positions were quantified using centroid-based measurements. The centroid position was calculated for both the tibial and femoral segmentations in each frame. In the sagittal plane view, the relative displacement between the femoral and tibial centroids was measured in two directions: anterior-posterior (horizontal in the image plane) and superior-inferior (vertical in the image plane).

To enable comparison across datasets with different ranges of motion, the device arm angle measured by the rotary encoder was normalized to a 'flexion percentage' scale, where -100% represents the minimum device arm angle (maximum knee flexion position), 0% corresponds to the maximum device arm angle (maximum knee extension position), and +100% marks the return to the minimum device arm angle (return to maximum flexion position).

3. Results and Discussion

The semi-automated tracking algorithm successfully tracked both the tibia and femur edges throughout the motion cycle for all five subjects, with a combined average alignment error of 0.40 ± 0.02 mm for both bones. **Figure 4** demonstrates the tracking results at different points in the motion cycle, showing the segmented bone contours overlaid on the original CINE frames. The semi-automated method required less than 5 minutes of processing time per dataset, compared to approximately 15 minutes needed for manual segmentation of all frames in a single dataset.

The The relative bone motion parameters extracted from both manual and semi-automated segmentation methods are shown in **Figure 5**. During knee extension, we observed a change in tibiofemoral angle of 24.10° ± 7.15° using the semi-automated method compared to 24.99° ± 8.20° with manual segmentation. The anterior-posterior translation measured -18.78 ± 3.16 mm and -18.95 ± 4.03 mm for semi-automated and manual methods respectively, while superior-inferior translation remained minimal (semi-automated: 0.82 ± 1.33 mm; manual: 0.53 ± 1.76 mm). As shown in **Figure 5**, the semi-automated method demonstrated consistently lower standard deviations across all parameters compared to manual segmentation, indicating higher precision and measurement reliability.

The kinematic values obtained in this study align well with previous reports using dynamic MRI [14,16]. These studies have reported comparable ranges of motion across all degrees of freedom during knee flexion-extension, with tibiofemoral angles, translations, and rotations falling within physiologically expected ranges. The alignment error of 0.40 ± 0.02 mm achieved by our tracking algorithm compares favourably to previously reported accuracies of bone tracking methods ranging between 0.33-0.97 mm [15].

The tracking accuracy of 0.40 ± 0.02 mm achieved by our algorithm demonstrates that reliable bone tracking is possible directly from 2D CINE MRI data of controlled knee motion. The consistently lower standard deviations in the kinematic parameters extracted using the semi-automated method compared to manual segmentation suggest enhanced measurement precision. Notably, the kinematic patterns showed strong symmetry between flexion and extension phases, though only extension phase values were reported in detail. This symmetry further supports the robustness of the tracking method across the complete motion cycle. This improvement in precision, combined with the substantial reduction in processing time, indicates that automated tracking approaches can both streamline analysis and potentially improve measurement reliability. The successful implementation of this tracking approach for 2D imaging provides a foundation for future development of similar principles for more complex 3D dynamic imaging applications.

4. Conclusion

We have developed and validated a semi-automated method for extracting tibiofemoral kinematics from 2D CINE MRI sequences acquired during controlled knee flexion-extension using a custom MR-compatible loading device. The algorithm successfully tracks bone motion by combining edge detection with connected component labeling, requiring minimal manual input and reducing processing time compared to manual segmentation. When compared to manual segmentation, the method showed lower variability in measuring tibiofemoral angle and translations across subjects. Future work should focus on extending these tracking principles to 3D dynamic imaging sequences to enable analysis of more complex knee motion patterns.

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