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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. 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 Unlike methods requiring 3D bone models, our technique operates directly on dynamic frames without requiring additional static scans, potentially streamlining the overall analysis process.. The primary objective was to develop and validate a bone tracking method that can reliably extract bone motion parameters directly from dynamic MRI sequences. To validate our approach, we compared centroid-based distance measurements between manual and semi-automated segmentation across all frames throughout the motion cycle, demonstrating that the developed 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 surface of the knee resting directly on it. The second coil was wrapped around the anterior surface 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 enabled CINE MRI, which continuously acquired 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 was created, effectively producing a ‘cinema’ of the joint motion.

Image reconstruction was based on 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°.The optical signals were first converted to electrical signals by a controller unit (MR330, Micronor), which were then sampled simultaneously with the electrical MRI scanner's sequence 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 complete 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 reconstruct the radially sampled k-space data. Specifically, the “Alternating Direction Method of Multipliers” algorithm within RIESLING was used, with “Total Generalized Variation” regularization [23,24]. 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 after reconstruction as compared to participants with a 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 [25]. 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 [26] 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". Full 3D connectivity was used, meaning pixels could be considered part of the same component if they were adjacent (including diagonally) either within a frame or across consecutive frames. This approach ensured that the same bone edge maintained a consistent label throughout the motion sequence, facilitating tracking across frames. . 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 [27]. The sorted points were then downsampled to 80 equidistant points using cubic spline interpolation [28]. 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 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 quantified the total distance between the transformed reference points (established along the bone edges in the initial frame) and the detected bone edges in the target frame, with a perfect alignment resulting in an output of 0. The goal was to find the combination of transformation parameters that minimize 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 [29]. 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 [30]. 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), and +100% marks the return to the minimum device arm angle (return to maximum flexion position).

The tracking accuracy was evaluated using the cost function described in section 2.2, which quantifies the distance between the transformed reference points and the detected bone edges. The cost function value divided by the total number of reference points provided an average alignment error in millimeters for each bone in each frame.

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 relative bone positions measured using both manual and semi-automated segmentation methods are shown in Figure 5. The relative displacement between bone centroids in the anterior-posterior direction measured -18.78 ± 3.16 mm and -18.95 ± 4.03 mm for semi-automated and manual methods respectively, while displacement in the superior-inferior direction 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 these measurements compared to manual segmentation, indicating higher precision and measurement reliability.

The ability to precisely quantify relative bone positions in healthy volunteers (n=5) demonstrates the technical feasibility of our bone tracking approach. As this study focused on algorithm development, establishing normative bone motion parameters and their variations across populations would be the subject of future dedicated studies.This capability could be particularly valuable for studying conditions that alter normal knee mechanics. Ligament injuries can affect joint stability, leading to increased laxity [31]. Additionally, these injuries can result in altered movement patterns during functional activities, as demonstrated in studies of ACL deficiency showing changes in tibial motion [6]. Our method's precision could potentially detect such subtle deviations from normal motion patterns. While the clinical interpretation of such differences would require careful validation in future studies with specific patient cohorts, the precision and efficiency of our tracking method makes it a promising tool for comparative analyses between normal and pathological joint motion patterns.

4. Conclusion

This study presents a novel semi-automated method for tracking bone motion in 2D sagittal CINE MRI sequences during controlled knee flexion-extension movements. The method significantly reduces processing time compared to manual segmentation while improving measurement reliability. The ability to efficiently quantify relative femoral and tibial positions during motion makes this approach valuable for analyzing joint movement patterns. This technical advancement contributes to the broader goal of understanding normal and pathological knee function through dynamic MRI analysis.

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