A Proximal Humeral Coordinate System Derived From Automatically Identified Landmarks Performs Comparably To Established Proximal Humeral Coordinate Systems

Jonathan D. Glenday[1], Lawrence V. Gulotta[1], Heath B. Henninger[2], Andreas Kontaxis[1]
[1] Hospital for Special Surgery, New York, NY. [2] University of Utah, Salt Lake City, UT.
glendayj@hss.edu

Disclosures: Glenday (N). Gulotta (2, 3B, 7A: Zimmer Biomet. 2, 7A: Exactech. 2: Smith & Nephew. 4: Imagen, Responsive Arthroscopy. 8: HSS Journal). Henninger (5: Stryker; Smith & Nephew). Kontaxis (N).

INTRODUCTION: Pre-operative computed tomography (CT) scans of the shoulder typically do not include the whole humerus. Consequently, the medial and lateral epicondyles of the distal humerus are not captured, thereby preventing the construction of a coordinate system (CS) of the humerus, as recommended by the International Society of Biomechanics (ISB) [1]. To address this issue, a prior study constructed proximal humeral CS from landmarks identified in the CT scan and applied an Average Rotation Matrix (ARM) to register the proximal humeral CS to the whole-bone ISB CS [2]. Typically, these landmarks are identified manually, which is a time-consuming process that can be susceptible to observer errors. Automatic landmark identification can improve accuracy by reducing these errors and is a crucial step towards automating personalized biomechanical shoulder model construction. Therefore, the goal of our study was to implement an automated landmark identification algorithm that can be used to construct an ARM-based proximal humeral CS and to benchmark the performance of the algorithm compared to manually identified landmarks.

METHODS: A dataset was obtained from an online repository (https://zenodo.org/records/14590062) that included 3D bone geometries and anatomical landmarks. 71 (39M/32F) whole humeri with either no or mild glenohumeral osteoarthritis (OA) were selected from this dataset for the study. The anatomical landmarks, defined in the CT CS, included the humeral head center (HHC), medial and lateral epicondyles (ME and LE), shaft cylinder top and bottom (SCT and SCB), shaft cylinder axis (SCA, defined by the line connecting SCT and SCB), lesser and greater tuberosity (LT and GT), and the Crest. A custom MATLAB (MathWorks, MA, USA) toolbox standardized the edge length of the 3D bone geometries to 2 mm and the HHC, ME, and LE landmarks were used to transform the geometries from the CT CS to the ISB humeral CS. Additionally, a proximal CS was defined using the HHC, SCA, and each of the LT, GT, and Crest landmarks. For each CS, the corresponding ARM, as defined by Sulkar et al. [2], was applied to establish the LT-ARM, GT-ARM, and Crest-ARM CS. Next, an algorithm, outlined by Negrillo-Cárdenas et al. [3], was implemented in MATLAB to automatically identify the HHC, ME, LE, SCA, and bicipital groove (BG) landmarks on each geometry. It uses an object-oriented bounding box (OOBB) to determine the initial alignment of each geometry based on its dimensions (Fig. 1A). Using this initial alignment, the spherical cap of the humeral head is extracted from the diagonal of a cube enclosing the humeral head and the HHC landmark is determined using a sphere fit (Fig. 1B). The ME and LE landmarks were defined as the most medial and lateral nodes of the distal portion of the geometry (Fig. 1B). The SCA was calculated by progressively slicing the diaphyseal portion of the geometry in the transverse plane and fitting a line to the centers of the circles that best fit the outline of the geometry in each plane (Fig, 1C). The BG landmark was extracted from the most concave point along the groove using curvature analysis (Fig. 1D). Like the manual approach, the automated HHC, ME, and LE landmarks established the CT to ISB transformation for each geometry and a proximal CS was defined using the automated HHC, SCA, and BG landmarks. To construct the BG-ARM CS, the proximal BG CS of each humerus was registered to the corresponding whole-bone ISB CS and the rotation matrix describing this registration was converted to a quaternion, averaged across the geometries, and converted from the average quaternion back to a rotation matrix. To benchmark algorithm performance, the automatically identified landmarks of each humerus were transformed into their respective CT CS and the distance between matching landmarks was calculated. Additionally, the mean absolute difference (MAD) was calculated between the rotations used to construct the manual and automated ISB CS and between the rotations used to construct the ISB CS and each LT-, GT-, Crest-, and BG-ARM CS.

RESULTS: Processing time was ~5 minutes per humerus (total: 5 hours and 55 minutes) for manual landmark identification and 4.6 s ± 1.1 s per humerus (total: 5 minutes and 27 seconds) for automated landmark identification (including edge length standardization). The average distance between the manual and automated landmarks was 1.1 mm for HHC (range: 0.4 mm – 2.7 mm), 1.4 mm for ME (range: 0.2 mm – 4.6 mm), and 1.8 mm for LE (range: 0.2 mm – 6.5 mm; Fig. 2A). The MAD between the coordinate system rotations was 0.1° around the X-axis (adduction-abduction; range: 0° – 0.4°), 1.1° around the Y-axis (internal-external rotation; range: 0° – 5.6°), and 0.1° around the Z-axis (flexion-extension; range: 0° – 0.5°). All proximal humeral CS performed similarly, with the Y-axis rotation producing the largest MAD, ranging from 8.2° ± 7.2° for Crest-ARM CS to 10.1° ± 8.8° for LT-ARM CS (Table 1).

DISCUSSION: The automated landmark identification algorithm identified the HHC, ME, and LE landmarks within 1.8 mm of the manually identified landmarks across a cohort of 71 humerus geometries, while requiring only ~1.5% of the time needed for manual identification. Identification of the ME and LE landmarks produced the largest variability, which can be attributed to methodological differences: the manual approach fits a cylinder to the epicondyles, whereas the automated approach identifies these landmarks as the medial and lateral extrema of the geometry, that has an initial OOBB alignment which may be sensitive to humeral version. Despite these differences, both approaches resulted in similar ISB registrations, with a MAD of 1.1° around the Y-axis. Regarding the registration of the proximal humeral CS to the whole-bone CS, the automated BG-ARM CS performed comparably to the manual LT-, GT-, and Crest-ARM CS, with all alignments producing a ~10° difference around the Y-axis. This difference is driven by the anatomy of the humerus as these landmarks are located on, or close to, the humeral head and are likely unable to account for humeral version. Additionally, curvature analysis required a uniform mesh density for adequate performance. Therefore, a mesh sensitivity analysis determined that a 2 mm edge length provided a sufficient trade-off between algorithm accuracy and processing time. It should also be noted that the algorithm cannot be used for a humerus with OA near to the bicipital groove as it negatively impacts the curvature analysis. Next steps will explore alternate methods of identifying the ME and LE landmarks to reduce variability and to extend the applicability of the algorithm to all OA types.

SIGNIFICANCE/CLINICAL RELEVANCE: Our study shows that a proximal humeral CS generated from automatically identified landmarks performs comparably to manually derived CS. This is an important step towards the automated construction of personalized shoulder models from pre-operative CT scans. These models have the potential to provide biomechanical insights that can inform individualized surgical planning and rehabilitation strategies.

REFERENCES: [1] Wu et al. J Biomech (2005). [2] Sulkar et al. Gait & Posture (2021). [3] Negrillo-Cárdenas et al. Med Image Anal (2020).

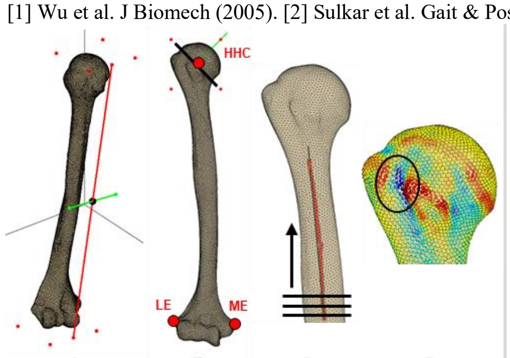

Figure 1

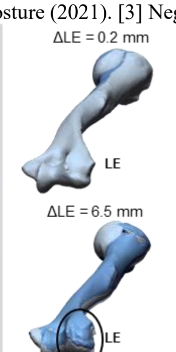

Figure 2

Table 1: Mean absolute difference between proximal and ISB coordinate systems

Metric	BG	LT	GT	Crest
ΔX (°)	0.8 ± 0.6	1.1 ± 0.9	1.1 ± 0.9	1.1 ± 0.9
ΔY (°)	9.6 ± 8.1	10.1 ± 8.8	10.8 ± 9.0	8.2 ± 7.2
ΔZ (°)	0.7 ± 0.7	0.9 ± 0.8	1.0 ± 0.8	1.0 ± 0.8

Figure 1: Automated landmark identification algorithm **A:** The red dots indicated the object-oriented bounding box. **B:** Identifying HHC by sphere fitting the region of the humerus above the black diagonal line. Identifying ME and LE as the extrema of the epicondyles **C:** Calculating SCA by best fitting a line to the center of circle fits in progressive transverse planes. **D:** Heatmap of curvature analysis used to identify the bicipital groove. Blue dots represent concave nodes. **Figure 2:** Differences between the best (top) and worst (bottom) automated alignments. **Table 1:** MAD between the ARM and ISB coordinate systems (mean ± SD).