Impact of CT Reconstruction Kernel on Image-Based Quantification of Fatty Infiltration in Shoulder Muscles

Hamidreza Rajabzaderh-Oghaz, Josie Elwell, Vikas Kumar, David Berry, Sandrine Polakovic, Chris Roche

Disclosures: Rajabzadeh-Oghaz, Elwell, Kumar: 3A-Exactech, Inc; Berry: Nothing to disclose;
Polakovic P: 3A-Exactech, Inc; Roche: 3A-Exactech, Inc. 4-Exactech Inc.

INTRODUCTION: Treatment planning and surgical outcome of shoulder arthroplasty rely heavily on the integrity and quality of bone, joints, and muscles. There is a growing number of image-based studies to characterize the quality of bone and muscles[1], [2]. For instance, studies have shown that fatty infiltration, defined as percentage of fatty tissue within the muscle, can be measured using CT scans by stratifying voxels to fat or healthy muscle based on their voxel values (known as Hounsfield Unit-HU). This is because various tissues and materials in the body have differential attenuation of X-rays, where denser material, such as bone or metal, tends to appear brighter with higher HU, while less dense materials, such as fat or air, tend to appear darker with lower HU.

Although CT scanners are routinely calibrated using reference materials like water and air, the resulting output images may vary depending on the specific scanner machines and acquisition parameters. For instance, different manufactures and health institutions might apply different reconstruction kernels, also known as a filter, to generate CT scan images. The choice of reconstruction kernel influences image quality, noise level, and the visibility of specific structures in the images [3] The impact of these CT scan parameters on image-based quantification of shoulder's bone and muscle characteristics is often underestimated. The objective of this study is to emphasize the importance of considering imaging parameters when quantifying metrics that are derivative of HU, such as fatty infiltration.

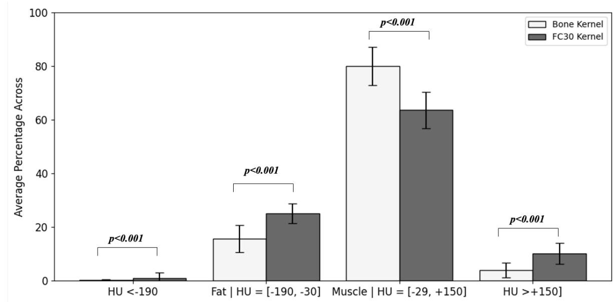

Figure 1: Average distribution of voxel within different HU bucket for two different kernels.

METHODS: A total of two hundred pre-operative CT images were collected from patients enrolled in a multi-center, IRB-approved database who underwent total shoulder arthroplasty using a single system (Exactech, Inc., Gainesville, FL). A hundred of the scans (50% female, average age of 70 ± 8, 76% with osteoarthritis, 12% rotator cuff tear, 15% rotator cuff arthroplasty) were acquired using GE Scanner and reconstructed using "Bone" Kernel, while the remaining 100 images (49% female, average age of 70 ± 8, 63% with osteoarthritis, 8% rotator cuff tear, 35% rotator cuff arthroplasty)) were scanned by Toshiba scanner and reconstructed using FC30 kernel. Utilizing a machine-learning based segmentation algorithm, the boundary of deltoid muscles was segmented in all images. Then, within the segmented area, voxels were stratified to four different classes based on their HU value: "low" if HU < -190, "fat" if HU falls within the range of [-190, -30], "muscle" if HU falls within the range of [-29, +150], and "high" if HU > +150 [4]. The distribution of voxels to different classes between images reconstructed by Bone and FC30 kernels were compared.

RESULTS: Figure 1 shows the average percentage of voxels stratified into different classes for both Bone and FC30 kernels. In general, the majority of voxels were classified as muscle, followed by fat class. The percentage of voxels which were classified to HU<-190 were negligible in both kernels. Comparing the two kernels, there was a significant difference in voxel percentage stratified to different classes. Using Bone kernel, less voxels were categorized as fat compared to FC30 [15.70% vs. 25.11%] and more voxels were categorized as muscle [79.99 % vs. 63.63%]. Additionally, for images reconstructed with FC30 kernel, 10.19% of voxels were classified as HU>+150, while it was only 4.06% in images reconstructed with Bone kernel. Figure 2 shows the voxel distribution for each of the four classes in two kernel methods. Notably, a substantial number of voxels (9.4%) are classified as HU>+150 in FC30 kernel. In contrast, only 0.4% of voxels were classified into HU>+150 class in image reconstructed with Bone kernel.

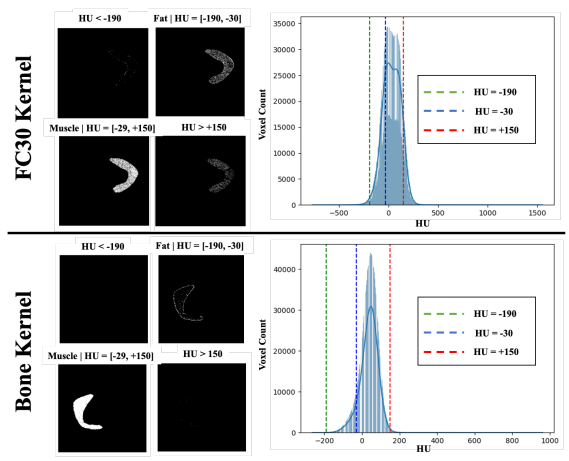

Figure 2: Voxel distribution of two image, reconstructed with a. Bone and b. FC30 Kernel.

DISCUSSION: The findings of this study highlight the impact of imaging reconstruction kernel on quantification of HU-derived metrics for soft tissues, such as fatty infiltration. This shows the need for post-imaging methods to ensure consistency in CT scans, such as normalizing CT data with varying kernels [5], and standardizing imaging protocols. Our study had several limitations, including utilizing only two kernels, impact of resolution on the image quality, Tube Voltage, etc. In addition, further studies are required to explore the reliability and impact of imaging parameters on other metrics like shape and radiomics.

SIGNIFICANCE/CLINICAL RELEVANCE: While CT scans, coupled with image-based analysis, have the capability to quantify bone and muscle characteristics, certain metrics such as fatty infiltration, could be impacted by image acquisition parameters, such as reconstruction kernel. Standardizing image with post-processing methods could improve reliability of such measurements and facilitate easy adoption of these metrics in clinical practice.

REFERENCES:

[1] G. Liu *et al.*, "Hounsfield units predicts the occurrence but not the patterns of proximal humerus fracture in the elderly patients," *BMC Musculoskelet Disord*, 2023.

[2] E. Taghizadeh *et al.*, "Deep learning for the rapid automatic quantification and characterization of rotator cuff muscle degeneration from shoulder CT datasets," *Eur Radiol*, 2021.

[3] T. Refaee *et al.*, "CT Reconstruction Kernels and the Effect of Pre-and Post-Processing on the Reproducibility of Handcrafted Radiomic Features," *J Pers Med*, 2022.

[4] J. Aubrey *et al.*, "Measurement of skeletal muscle radiation attenuation and basis of its biological variation," *Acta physiologica*, vol. 210, no. 3, pp. 489–497, 2014.

[5] L. Gallardo-Estrella *et al.*, "Normalizing computed tomography data reconstructed with different filter kernels: effect on emphysema quantification," *Eur Radiol*, 2016.