AI BASED 3D ANALYSIS OF GLENOID BONE LOSS

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Introduction

Glenoid rim defects affect the glenoid concavity increasing the risk of recurring instability [1]. Treatment planning currently considers 2D measures of bone loss that tend to over- or underestimate the defect size [2], and do not consider the impact of glenoid concavity on glenohumeral stability [3]. Recent developments in AI enable accurate automatic segmentation of the shoulder bones for 3D analysis [4], however, 3D bone loss analysis additionally requires knowledge of the premorbid glenoid morphology. For improved shoulder instability analysis from medical images, we hypothesized that a deep learning network could be used to predict the premorbid shape of the glenoid to allow for an automatic and accurate calculation of the missing surface area of the defect and the glenoid concavity.

Methods

Data: The scapula was manually segmented from 55 CT images (bilateral shoulder, plane resolution: (0.42-0.99mm), slice thickness (0.30-0.90mm)) of patients with intact glenoids (KEK: CCER 2020-02670). Three landmarks on the lower glenoid rim and one on the superior glenoid tubercle were manually picked on the resulting scapula surface models. Artificial glenoid defects (10 per patient) of varying shapes, sizes and locations were created by subtracting the overlapping portion of a sphere (radius 45-60mm) from the glenoid rim. Trained network: The data was split into training (N=36) and test sets (N=19). A shape completion network was trained using the nnU-Net framework [5] with the paired complete glenoid models and corresponding models with simulated defects. Glenoid analysis: Using the manually placed landmarks on the surface model, the glenoid rim was defined and the 3D surface area calculated. The bone loss was calculated as the percentage of missing glenoid surface area and concavity as the radius of a sphere fitted to the surface mesh of the lower glenoid. The accuracy of our method (calculated relative to the ground truth) was compared to a 3D contralateral shoulder model as an estimate of the premorbid glenoid.

Results

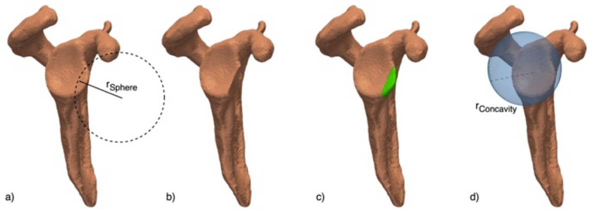

Figure 1: Segmented 3D scapula models: a) With sphere, process of simulated defect creation. b) With simulated defect. c) With predicted glenoid (green). d) With fitted sphere to lower glenoid to calculate glenoid concavity.

Our proposed AI based method was significantly more accurate than the use of the contralateral shoulder for calculating glenoid bone loss (mean error of -1.75 ± 2.22% versus -11.12 ± 12.01%), glenoid concavity (mean error of 0.02 ± 0.88 mm versus -0.52 ±3.31 mm).

Discussion

Our proposed deep learning-based method for 3D quantification of glenoid bone loss predicted the native glenoid with higher accuracy than the contralateral shoulder, facilitating automatic and accurate 3D analysis of glenoid defects. Simulated defects allowed for accuracy validation to the ground truth. Future work will validate the method on defective glenoids, extend it to MRI, and assess image-based instability measures using biplanar radiographic imaging (DBRI).

References

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