Impact of Deep Learning based Image Quality Augmentation on CBCT based Radiomics Analysis

Mi Huang[1], Zeyu Zhang[1], Jessica Lee[1], Zhuoran Jiang[1], Tianye Niu[2], Fang-Fang Yin[1], Lei Ren[1]

1. Duke University Hospital Cancer Center, Department of Radiation Oncology, Durham, NC
2. Georgia Institute of Technology, Department of Nuclear Engineering Atlanta, GA

Duke University School of Medicine

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INTRODUCTION

To investigate the impact of image quality of CBCT on Radiomics analysis.

AIM

CBCT provides important information of patient anatomy and radiomics textures during the treatment course, which can be valuable for predicting the treatment outcome. However, CBCT has very limited image quality due to scattering, beam hardening, motion, or under sampling, which makes it questionable if CBCT can be reliably used for radiomics analysis. In this study, we aim to address this critical question by investigating the impact of CBCT image quality on radiomics analysis. Specifically, we employed our recently developed deep learning model to substantially augment the image quality of CBCT and investigated the effects of such augmentation on the radiomic features extracted from the images.

METHOD

A deep learning GAN model was developed for CBC augmentation. We used eight SBRT patients' lung CBCT images as training data set. The plan CT was registered to each fraction CBCT. We then use the CycleGAN model to augment CBCT to match with the registered CT. Once trained, the model was used to augment the CBCT from 3 testing patients. The ROI Radiomics were calculated for the plan CT, original CBCT, and augmented CBCT for each fraction of each patient.

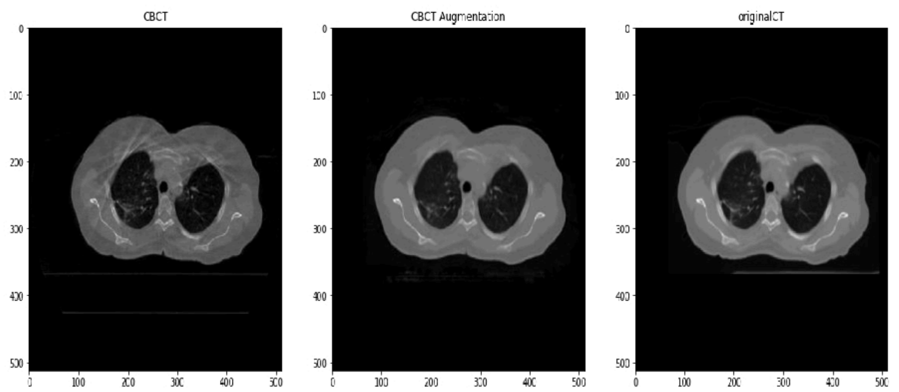
For radiomics analysis, all radiomics features of the pCT and CBCT VOIs on each fraction of the patient were extracted from the Gross Tumor Volume (GTV) of each fraction of the lung cancer patient.

RESULTS

The feature pool consisted of 7 histogram features, 22 gray level co-occurrence matrix (GLCM) features, 13 gray-level run-length matrix (GLRLM) features, 13 gray level size-zone matrix (GLSZM) features, 5 neighborhood gray-tone difference matrix (NGTDM) features, 480 wavelet-based radiomics features, and 7 shape features.

The interclass correlation were calculated for each zone of Radiomics features of each fraction and for each patient, cross all features for comparison. The cross correlation between CBCT and CT features improved from 0.896, 0.810, 0.901 in original CBCT to 0.899, 0.974, 0.961 in augmented CBCT for the three patients. In all radiomics zones, especially in GLCM features, the improvement of image quality improve the correlation of the CBCT images to Plan CT, which used widely for Radiomics analysis. During all fractions, the correlation of the Augmented CBCT to original CBCT was consistent and were all above 0.9. The sensitivity of features against image quality was consistent among different days' CBCT. The same trend was observed across all three patients.

Figure 1. Left(L): Original CBCT of SBRT Lung patient fraction1; Middle(M): Augmented CBCT (Post-CBCT); Right(R): Original Plan CT image



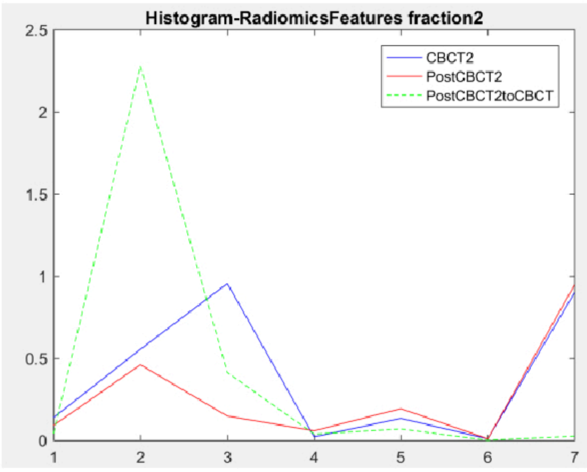


Figure2: Zone1 Histogram Radiomics features of fraction 2 CBCT images (CBCT2: commercial CBCT Radiomics features (blue); PostCBCT2: Augmented CBCT with deep learning scatter correction (Blue). PostCBCTtoCBCT (Green): ratio of radiomics features of Postprocessed CBCT to original CBCT . All features were taking original CT images as ground truth. Augmented CBCT (red) was closer to ground truth.

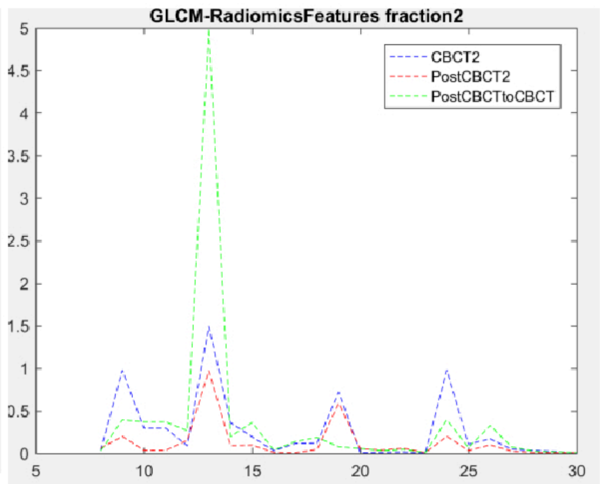


Figure3: Zone2 GLCM Radiomics features of fraction 2 CBCT images (CBCT2: commercial CBCT Radiomics features (blue); PostCBCT2: Augmented CBCT with deep learning scatter correction (Blue). PostCBCTtoCBCT(Green): ratio of radiomics features of Postprocessed CBCT to original CBCT . All features were taking original CT images as ground truth. Augmented CBCT (red) was closer to ground truth.

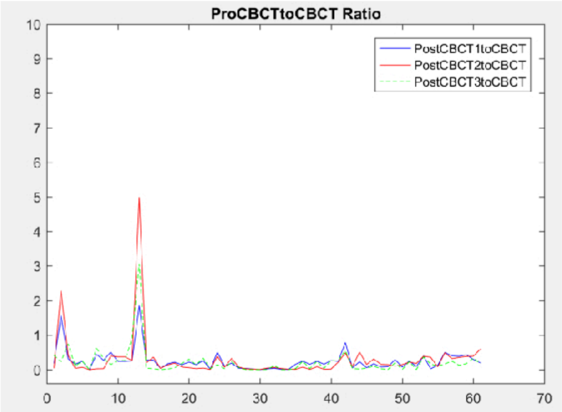


Figure 4: The daily fraction Post-CBCT to CBCT of Patient 1. Fraction1 to fraction3 Radiomics features ratios, CT as ground truth.

GTV Radiomics Features	Mean	Variance	Correlation ProCBCT/CBCT
Post CBCT/CBCT Fraction1	0.41	0.75	0.97
Post CBCT/CBCT Fraction2	0.30	0.23	0.88
Post CBCT/CBCT Fraction3	0.29	0.63	0.95

Table1. The daily fraction Post-CBCT to CBCT of Patient 1. The highly correlated relationship is consistent from fraction to fraction, and for the first 61 features the post-processing is consistent with original CBCT (highly correlated).

CONCLUSIONS

Image quality can significantly impact radiomics analysis using CBCT. Image quality augmentation is vital for establishing accurate and robust CBCT based radiomics related studies, due to scatter correction.

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CONTACT INFORMATION

Mi Huang, PhD
Duke University Radiation Oncology
Work.mimi@gmail.com