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Assessment of Anatomical Changes on Cone Beam Computed Tomography During Radiation Therapy Using TensorFlow-Based AI

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ABSTRACT

Purpose: This study developed an AI model to distinguish anatomical changes and quantify variations in patient alignment on cone beam computed tomography (CBCT) images between fractions of external beam radiation therapy treatments.

Methods: A TensorFlow based 3D-Unet model was developed and trained to recognize the differences between CBCT scans. Training data was generated by creating known augmentations that mimicked clinically relevant transformations. These transformations consisted of shifts, rotations, and scales of different magnitudes. The model was trained in three phases. Phase one trained the model to recognize segmentation and similarity, phase two focused on learning classification of transformations, and phase three enabled estimation of transformation magnitude. Evaluation of the model was done using a specifically designed dataset.

Results: The model was trained on 1,409 pairs of CBCT scans for previously treated prostate patients. Training consisted of 10 epochs and an 80%/20% learning to validation split. Heat maps were generated and demonstrated near identical agreement for the true and predicted difference. The model had strong performance in segmentation with DICE coefficients consistently around 0.90 and as high as 0.97. The predicted similarity score showcased the model's capability to detect and flag large anatomical changes. It was able to successfully identify transformations 85.8% of the time as well as quantify the magnitude of the transformation 73.4% of the time during training.

Conclusion: An AI model with these capabilities has the potential to automate intrafraction review of patient alignment and anatomy. The model provides metrics that give medical professionals quantitative information to make clinical decisions. Further expansion and training of the model has potential to guide adaptive workflows during patient treatments.

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INTRODUCTION

Cone beam computed tomography (CBCT) is commonly used in radiation therapy to verify patient positioning and anatomy before treatment[1]. Target margins are often within millimeters, therefore small anatomical changes or setup deviations can have clinical implications[2]. A major challenge in conventional radiation therapy is determining when to replan or adapt an existing treatment plan. The determination of when these circumstances warrant adaptation is based on image review. Current assessment of these changes relies primarily on visual inspection which introduces subjectivity and variability into clinical decisions. This work investigated if TensorFlow-based AI model could provide quantitative assessment of anatomical changes and setup errors between two CBCT images to support image-guided and adaptive radiation therapy workflows[3].

METHODS AND MATERIALS

A TensorFlow based model with a two-channel input was developed with a 3D-U-net architecture to compare two different CBCT image sets[4,5]. Datasets from two different prostate patients were used. Each patient contained CBCT images from 28 fractions. One was used to train the model and the other was used during evaluation. Training data was expanded through augmentation using shifts (2-20 pixels), rotations (2-20°), and scaling (0.85-1.15x) to simulate clinically relevant errors. A developed pairing algorithm created 1,409 pairs for training. The model was trained in three phases sequentially for similarity and segmentation, transformation classification, and magnitude estimation. Generated outputs included a heat map of the predicted differences, similarity score, classification of the transformation, and estimation of the magnitude of change.

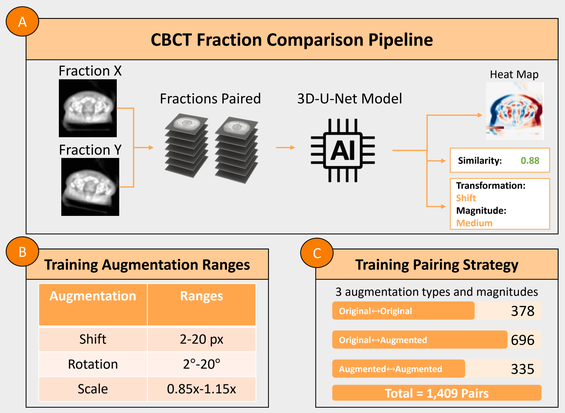

Figure 1. Overview of the CBCT fraction comparison pipeline and training design. **A)** DICOM image sets from two fractions are preprocessed and paired then entered through the 3D-U-Net Model resulting in a heat map, similarity score, as well as transformation and magnitude estimation. **B)** Augmentations (shift/rotation/scale) applied to training data and their ranges. **C)** Structured pairing strategy yielding 1,409 training pairs total.

RESULTS

- Predicted similarity mirrored true similarity trends closely, with a systematic offset typically ~0.05–0.10 lower than the computed ground truth
- Dice coefficient scores were consistently strong (often >0.90)
- During training, transformation type accuracy reached 85.8% and magnitude accuracy 73.4% although it sometimes misclassified the transformation and magnitude during evaluation
- For large setup errors, predicted similarity showcased lower similarity scores and better highlighted regions of deviation than true similarity, aligning with the intent to flag clinically important changes (e.g., 20-pixel shift interpreted as ~20 mm, exceeding typical 6–8 mm margins)
- Figure 1 shows the generated heat map and metrics.
- Figure 2 shows similarity score trends for different magnitude rotations.

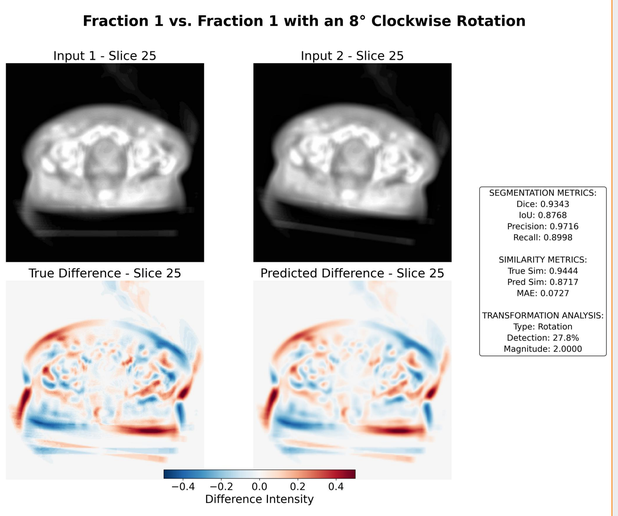

Figure 2. Heat map of the model output with metrics.

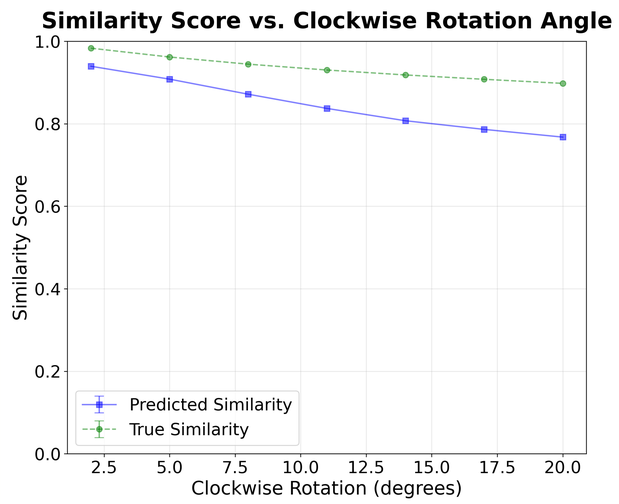

Figure 3. Predicted vs true similarity for different magnitudes of clockwise rotations.

DISCUSSION

The model consistently identified differences between the compared CBCT acquisitions. Predicted similarity score trends mirrored the true similarity score trends but consistently provided a lower predicted similarity score on large clinical deviations. This may exhibit that the model learned patterns and was able to provide a score more reflective of the true consequences of the changes. The segmentation scores along with the heat map allow for further identification of any underlying issues. Overall, the transformation classification and magnitude estimation performed well, but did result in some misclassifications and incorrect estimates during some of the evaluations. Clinical implementation would require further refinement of the model and retraining on an increased dataset. Performance indicated that AI models used for CBCT image comparison offer valuable insights for adaptive workflows and image guided radiation.

CONCLUSIONS

A TensorFlow-based AI model with a 3D U-Net architecture was developed that successfully provided a form of quantitative validation for comparison of two CBCT scans from different fractions. The model showed strong performance compared to the ground truth and clinically interpretable data. This paradigm has applications for identifying errors in patient setup, flagging anatomical changes, and providing more objective criteria for clinical decision making. Future work would aim to add a larger amount of patient datasets, more disease sites, and integration into the clinical workflow.

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