JULY 12–16 2020 VIRTUAL
JOINT AAPM | COMP MEETING
EASTERN TIME [GMT-4]

Synthetic Digital Reconstructed Radiograph for MR-only Robotic Radiosurgery with Deep Convolutional Adversarial Networks

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INTRODUCTION

As radiation therapy moves towards MR-only treatment planning, it is vital to be able to generate high quality synthetic CTs from the acquired MRI images for accurate dose calculation and target localization. Several techniques have been demonstrated to generate synthetic CTs, using atlas-based mapping or machine-learning [1-3]. Some treatment methods, such as robotic radiosurgery, require the visualization of implanted fiducials for verification of proper patient positioning, and these are not easily seen on traditional MRI images. However, recently developed MR sequences have shown promising results in localizing fiducials on MRI images [4-5]. Based on this, we have developed a machine learning model capable of creating synthetic CTs and DRRs that include fiducial information, demonstrating the feasibility for an MR-only workflow for fiducial-based treatments.

AIM

To create a machine learning model capable of creating synthetic CTs and DRRs that allow for the accurate visualization for implanted fiducials from MRI images created using a fiducial-enhancing MR sequence.

METHODS

To create synthetic CTs of images containing fiducials, we developed a deep convolutional adversarial network which used a Fully Convolutional Network (FNC) as the generator and a Convolutional Neural Network as the discrimination. A detailed description of the network can be found in Nie et al. [6] The network structure can be seen in figure 1, below. We then trained the network using 11 MR/CT rigidly registered image pairs from prostate patients previously treated on CyberKnife. As our MR images were not acquired using the fiducial enhancing sequence, we artificially adjusted the pixel values in the area of the fiducials to match the contrast of this type of sequence. Using a testing set, we generated synthetic CTs and DRRs at four angles (a 45/315 pair, as would be used in a Cyberknife treatment, and a 0/90 pair, as would be used on a conventional linac treatment). The similarity between the true and synthetic DRRs was evaluated using the mean squared error (MSE) and the peak signal-to-noise ratio (PSNR). to evaluate the accuracy of fiducial localization, a group of five observers were asked to identify the center of fiducial on the ground truth and synthetic DRRs.

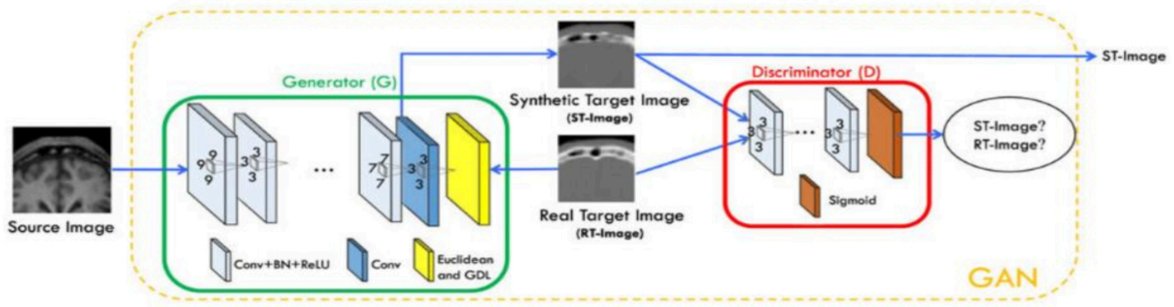

Figure 1: *Architecture of the adversarial network used to generate synthetic images*

RESULTS

Across the 4 testing sets (4 DRRs per set, a total of 16 images) the mean MSE was **1.2±1.5%** and the mean PSNR was **22.8±5.7**. The five observers on average identified the same number of fiducials (difference of **0.05±0.68** fiducials identified between the true and synthetic DRRs) and identified the centers within **1.4±0.96 mm**. Two image pairs were found to have poor visualization of the fiducials in both the true and synthetic DRRs; excluding these pairs, the average distance between the identified fiducial centers drops to **0.89±0.09mm.**

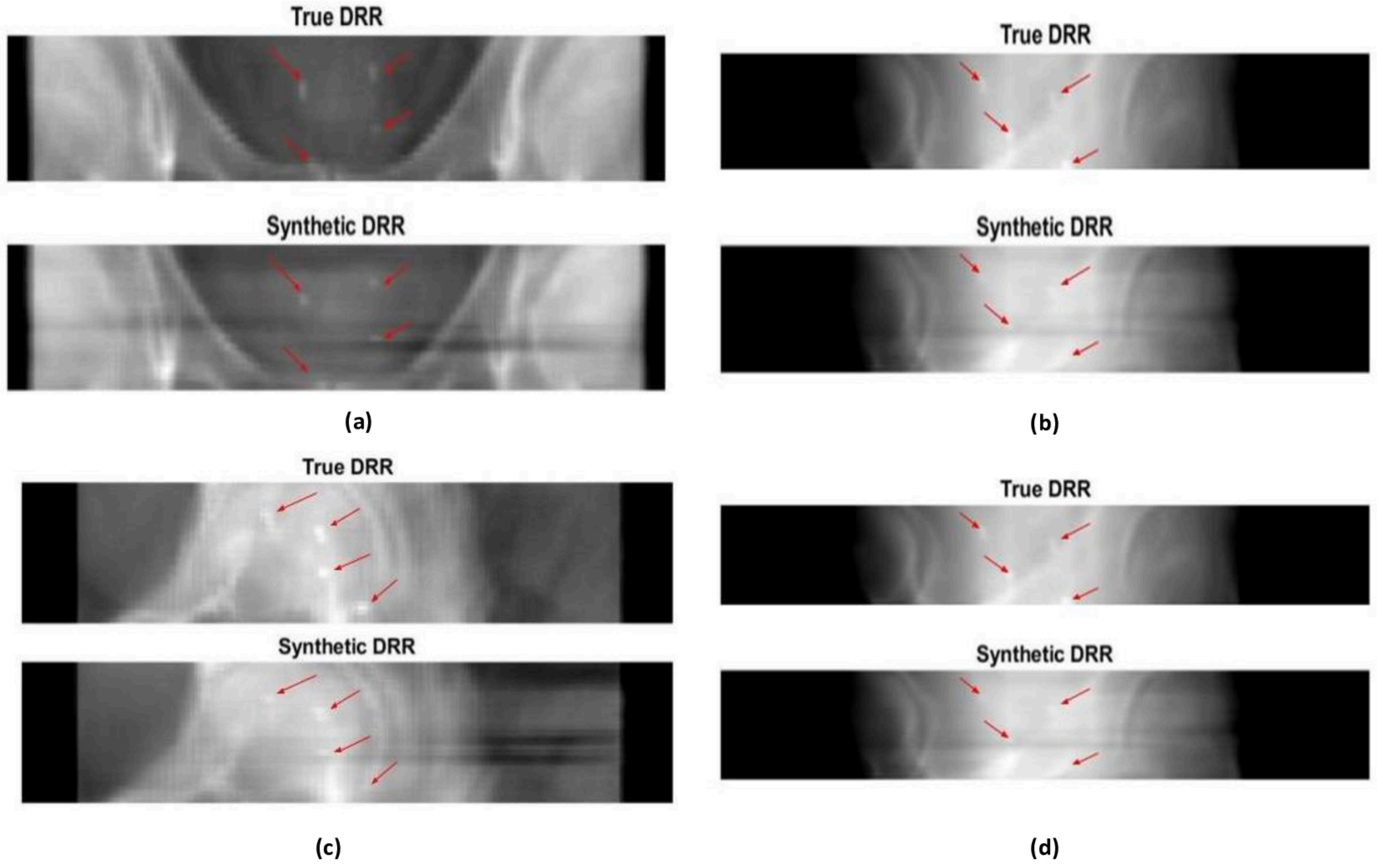

Figure 2: *Comparison of the true and synthetic DRRs for an example case across the four angles tested; 0 (a), 45 (b), 90 (c) , and 315 (d) degrees. Red arrows point to the location of the four implanted fiducials*

CONCLUSIONS

We have developed a machine learning model that is capable of reproducing fiducial information on synthetic CTs and DRRs from MR data. **For all cases tested, synthetic DRRs provided similar visualization of implanted fiducials as DRRs created from ground truth data**. This makes it possible to carry out MR only planning and treatment for fiducial based robotic radiosurgery.

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ACKNOWLEDGEMENTS

We would like Dr. Zhengwang Wu and Ben Aycock for their help setting us up on the UNC BRIC GPU servers

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