A Clinically Deployable CT Synthesis Pipeline For Radiotherapy Planning From Clinical MRI Sequences

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INTRODUCTION: Medical imaging plays an important role in radiotherapy by allowing more precise diagnosis and treatment planning of patients with musculoskeletal tumors (in connective tissues such as cartilage and bone). Computed tomography (CT) is primarily used for the radiotherapy due to its ability to provide accurate and high-resolution patient geometry, and enable direct electron density conversion needed for dose calculations. In the last decades, magnetic resonance imaging (MRI) has also proven its added value for tumors and organs-at-risk delineation from its superb soft-tissue contrast. MRI can be acquired to simulate the treatment planning to monitor changes before, during, or after dose delivery. Although MRI offers the complementary advantages, it requires CT registrations before the treatment phase to evaluate the treatment process. Such workflow requires additional CT scannings, increases workload, and introduces additional radiation to the patient. Recently, MRI-only-based radiotherapy has been proposed to simplify the process as well as minimize patients' exposures to ionizing radiation, which is particularly relevant for repeated simulations on fragile young populations. MRI-only radiotherapy may reduce overall treatment costs and workloads, and eliminate residual registration errors when using both imaging modalities. The main obstacle in utilizing MRI-only radiotherapy is the lack of tissue attenuation information required for accurate dose calculations. Here, we developed and trained a deep learning pipeline to synthesize 3D CT scans from clinical MRIs to not only expedite the treatment process but also minimize the radiation burdens for patients. We further test the pipeline's performances across a range of pelvis MRIs obtained from internal and external sources with different image acquisition parameters and filed of views (FoVs).

METHODS: A modified 3D CycleGAN model was trained and tested on 570 pairs of 3D MR and CT scans with varying FOVs. Among the 570 pairs, 360 pairs were internal data, which were acquired as a part of routine clinical care of patients (age: 5-58) with a range of hip disorders and degrees of skeletal maturity. The remaining 210 pairs were anonymized external data (age: 3-93) from three Dutch university medical centers (SynthRAD2023 Challenge). Our internal MR scans were collected using two clinical MR sequences (T1-VIBE and T1), whereas the external MR images consisted of T1 and T2 sequences. All imaging data underwent the same preprocessing steps, including resampling to an isotropic resolution of 0.5 mm, signal normalization, N4-bias correction (MR images only), and data augmentations (during the training phase). The dataset was split into training (~83%; n=473) and test set (~17%; n=87, registered MR-CT volumes). During the training phase, we used 305 registered pairs of MR-CT volumes and 168 unregistered pairs from different subjects with the same age and sex to account for potential variations in anatomy and skeletal maturity. We evaluated the performance of our pipeline by comparing real and synthetic CT volumes through mean absolute error (MAE) and peak signal-to-noise ratio (PSNR) for each sequence (ANOVA with Bonferroni posthoc).

RESULTS: The synthesized CT scans showed comparable appearances to the original CT scans (Figure 1A). In most cases, the pipeline had acceptable performances in synthesizing CT scans across all sequences from T1-Vibe volumes (MAE: 126.15 ± 15.69 and PSNR: 22.31 ± 1.76), internal T1 volumes (MAE: 74.79 ± 15.69 and PSNR: 25.71 ± 1.24), external T1 volumes (MAE: 72.91 ± 12.18 and PSNR:27.44 ± 1.21), and external T2 volumes (MAE: 67.61 ± 10.68 and PSNR: 28.23 ± 1.47); Figure 1B.

DISCUSSION: The proposed CT synthesis pipeline successfully generates realistic-looking CTs from clinical MRIs with adequate anatomical and attenuation profile accuracy. Literatures on radiotherapy planning using synthetic CT report MAEs from 27 to 65 HU for the entire body with PSNRs ranging from 24 to 34 dB. A few studies also present SSIM, which generally ranges from 0.87 to 0.99, as an additional evaluating metric. However, there have been some concerns about using SSIM for medical image analyses due to its inconsistent performances and results throughout the multiple studies. Thus, in this study, we mainly focus on MAE and PSNR to evaluate our model. Most previous studies only use a single MR sequence with lower resolutions and/or confined FOVs. In contrast, our model can synthesize CT scans from multiple MR sequences with higher resolutions and larger FOVs. While the CTs synthesized from T1-VIBE (large FoV) had lower performance, it was still within the reported error range. Our metrics and similar performance across different sequences highlight the robustness and generalizability of the developed pipeline. Such generalizability is critical for the clinical deployment of this pipeline, in particular in multi-site settings. We are currently working on expanding the pipeline to other anatomical regions as well as other MR sequences.

SIGNIFICANCE: A robust deep learning pipeline that can synthesize CT scans from clinical grade MRIs can help with patient-specific treatment planning for patients with tumors undergoing radiotherapy with minimum logistical burden and lowered radiation.

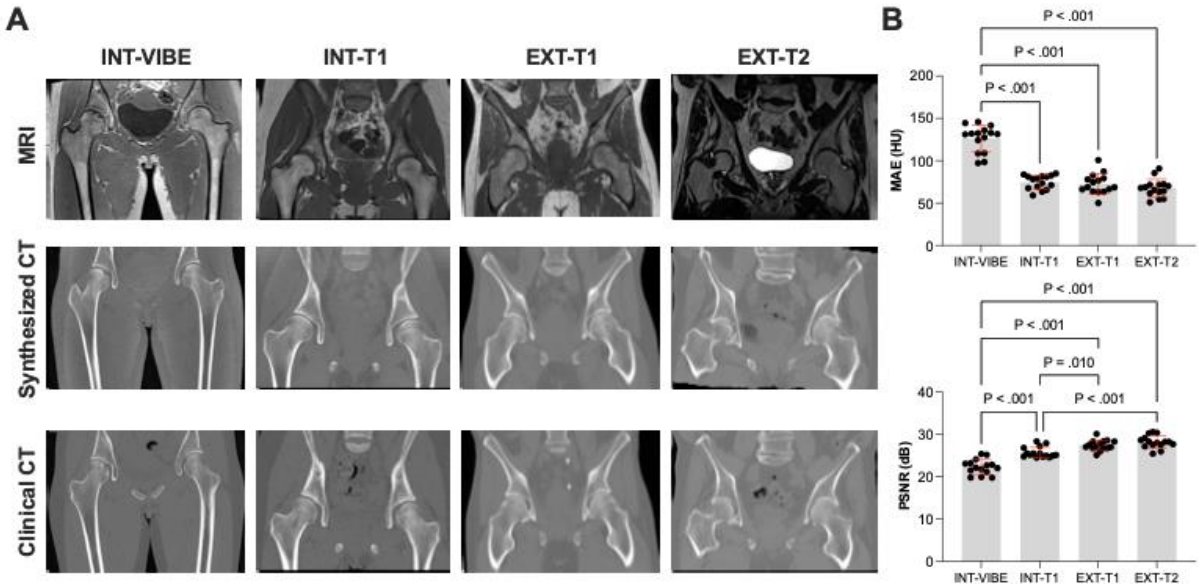

Figure 1. (A) Synthetic CT from multiple clinical MR sequences compared to original CT scans. (B) Performance metrics (MAE and PSNR) computed between synthetic CT volumes and corresponding original CT volumes.