MR to CT Translation with CNNs and GANs

Bodo Kaiser[1] and Shadi Albarqouni[2]

[1]Ludwig-Maximilians-Universität München
[2]Technische Universität München

January 2, 2018

Abstract

1 Introduction

Modern cancer treatment incorporates computer tomography (CT) and magnetic resonance tomography (MR) as the main imaging modalities. Radiation therapy (RT) and CT are based on the interaction of high energy photons (x-rays) with biological tissue, therefore so called image guided planning based on the patients CT scan is used to estimate the patients specific radiation treatment planning. Even though x-rays used for imaging are of a lower energy band as x-rays used for cancer treatment, it has been shown that they still possess a risk of developing new cancer inside the patient [13]. MR on the other hand takes advantage of the magnetic properties of hydrogen and is not associated with any health risks [8]. Furthermore MR provides a much higher soft tissue contrast which is useful for cancer classification. Although MR and CT differ significant in the applied physics the high entropy in MR data suggests the existence of a one directional mapping from MR to CT space whereby the acquisition of CT would become obsolete. Beside the stated health benefits for the patients such an approach would reduce expanses and also would free CT resources for emergency cases where the fast acquisition of CT is used to locate internal bleedings.

2 Related Work

Since the early days of CTs health manufacturer were attempted to reduce radiation exposure in CT scans by using i.e. more sensible detection electronics and more sophisticated scanning sequences. Through the growing availability of computing power we also find evermore computer vision techniques being utilized, for example to enhance the image quality of low-dose CTs [19]. Altough these efforts have lead to an impressive and steady evolution of CT apparatus, they still require the patient to be irradiated.

First approaches which dispense with radiation exposure, relay on the atlas based transformations applied to MR to predict CT [9]. Further improvements included i.e. random forests [1]. It has been shown that CT prediction can in fact replace CT for treatment planning [2].

In computer science we have seen an incredible progress with deep learning techniques in a variety of areas including natural language processing and computer vision [12]. Recent efforts with generative adversarial networks (GANs) [7] seem to be a promising path towards the challenge of finding appropriate target functions to optimize through the use of game theory. Successful applications in computer vision in which GANs proved significant improvements over the former state of art include the task of image to image translation [10] but also the generalization of three dimensional structures inside the so called latent space [18].

This in mind the medical computer vision community rapidly adapted GANs for their own specific tasks which in comparison to computer vision typical involve volumetric single channel images with high bit depth. Bearing the challenge of CT from MR prediction the expectations towards GANs have been met showing overall better results compared to the previous approach [15]. Additionally the full potential of GANs have not been exhausted yet as it also has been shown that GANs are capable of being trained with unregistered modalities [17].

Beside the enourmous breakthroughs made in medical computer vision we still see a shortage in a reproducable comparison of recent methods with publicly available data. Not to mention the open questions with regard to best practices in choosing good GAN model parameters for the task of CT prediction which we hope to address in the subsequent sections.

3 Method

In the consecutive parts we discuss the parameters relevant for the conducted experiments. This includes decisions we made for the setup as a whole (dataset, pre processing) but also detail decisions regarding for example the implementation of a specific model. The source code based on the Tensorflow framework [14] will be made available through GitHub after acceptance.

3.1 Data

We used the publicly available dataset from RIRE [5] which contains contains multi modality data of about 19 patients from which a subset of 17 patients have a complete pair of T1 weighted MR and CT volume.

We were able to co-register the modalities using [6] and the highest interpolation order. In the same step we also resliced the volumes to have a homogenous voxel size as the RIRE dataset has only a low resolution in the sagittal plane.

Finally we used [4] to load the aligned volumes and convert them into Tensorflow's tfrecord format and split them into a validation set of 4 and a training set of 13 patients. Inside the tensorflow input pipeline we normalized the value range of each volume to $[0, 1]$. For two dimensional models we padded the horizontal slices to 384×384. For three dimensional models we used $260 \times 340 \times 360$ (Depth x Height x Width).

3.2 Network

As generative adversarial networks we decided to use pix2pix [10] as it has already shown great results in the task of color image to image translation and context-aware 3d synthesis [15] which uses a simpler generator but accounts for 3d structures.

As convolutional encoder-decoder network we chose u-net [16] as it was able to compete with much larger models in the task of semantic segmentation [3]. Further our implementation of pix2pix uses u-net as generator network, hence we are able to evaluate the impact of the adversarial min-max approach.

Eventually we want to evaluate a new network and training approach novel to medical computer vision [11].

3.2.1 U-Net

3.2.2 Pix2Pix

3.2.3 3D Synthesis

3.3 Losses

3.3.1 Distance Losses

As norm losses we refer to the mean absolute error ($L1$ loss) and the mean squared error ($L2$ loss).

3.3.2 Gradient Losses

The gradient (difference) loss is used in the framework of context-aware 3d synthesis [15] in addition to the norm loss.

3.3.3 Signal Losses

From signal processing PSNR, SSE...

3.3.4 Adversarial Loss

Least-squared adversarial loss, standard adversarial loss. BEGAN loss ?

3.4 Augmentation

3.4.1 Random Crop

3.4.2 Rotation

3.4.3 Contast Adjustment

4 Results

4.1 Losses

4.2 Augmentation

5 Conclusion

References

[1] D. Andreasen. *Creating a Pseudo-CT from MRI for MRI-only based Radiation Therapy Planning.* DTU supervisor: Koen Van Leemput, Ph.D., kvle@dtu.dk, DTU Compute. Matematiktorvet, Building 303-B, DK-2800 Kgs. Lyngby, Denmark, 2013. URL: `http://www.compute.dtu.dk/English.aspx`.

[2] Daniel Andreasen and Koen Van Leemput. "An Investigation of Methods for CT Synthesis in MR-only Radiotherapy". PhD thesis. 2017.

[3] Vijay Badrinarayanan, Alex Kendall, and Roberto Cipolla. "SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation". In: *CoRR* abs/1511.00561 (2015). arXiv: `1511.00561`. URL: `http://arxiv.org/abs/1511.00561`.

[4] Matthew Brett et al. *nipy/nibabel: 2.2.0.* Oct. 2017. DOI: `10.5281/zenodo.1011207`. URL: `https://doi.org/10.5281/zenodo.1011207`.

[5] J. Michael Fitzpatrick. *RIRE - Retrospective Image Registration Evaluation.* 1998. URL: `http://www.insight-journal.org/rire/`.

[6] J. Michael Fitzpatrick. *SPM12 - Statistical Parametric Mapping 2012.* 2012. URL: `http://www.insight-journal.org/rire/`.

[7] I. J. Goodfellow et al. "Generative Adversarial Networks". In: *ArXiv e-prints* (June 2014). arXiv: `1406.2661 [stat.ML]`.

[8] Valentina Hartwig et al. "Biological effects and safety in magnetic resonance imaging: a review". In: *International journal of environmental research and public health* 6.6 (2009), pp. 1778–1798.

[9] Matthias Hofmann et al. "MRI-based attenuation correction for PET/MRI: a novel approach combining pattern recognition and atlas registration". In: *Journal of nuclear medicine* 49.11 (2008), pp. 1875–1883.

[10] Phillip Isola et al. "Image-to-Image Translation with Conditional Adversarial Networks". In: *CoRR* abs/1611.07004 (2016). arXiv: `1611.07004`. URL: `http://arxiv.org/abs/1611.07004`.

[11] Tero Karras et al. "Progressive Growing of GANs for Improved Quality, Stability, and Variation". In: *CoRR* abs/1710.10196 (2017). arXiv: 1710.10196. URL: http://arxiv.org/abs/1710.10196.

[12] Yann LeCun, Yoshua Bengio, and Geoffrey E. Hinton. "Deep learning". In: *Nature* 521.7553 (2015), pp. 436–444. DOI: 10.1038/nature14539. URL: https://doi.org/10.1038/nature14539.

[13] Diego R Martin and Richard C Semelka. "Health effects of ionising radiation from diagnostic CT". In: *The Lancet* 367.9524 (2006), pp. 1712–1714.

[14] Martın Abadi et al. *TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems*. Software available from tensorflow.org. 2015. URL: https://www.tensorflow.org/.

[15] Dong Nie et al. "Medical Image Synthesis with Context-Aware Generative Adversarial Networks". In: *CoRR* abs/1612.05362 (2016). arXiv: 1612.05362. URL: http://arxiv.org/abs/1612.05362.

[16] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. "U-Net: Convolutional Networks for Biomedical Image Segmentation". In: *CoRR* abs/1505.04597 (2015). arXiv: 1505.04597. URL: http://arxiv.org/abs/1505.04597.

[17] Jelmer M. Wolterink et al. "Deep MR to CT Synthesis using Unpaired Data". In: *CoRR* abs/1708.01155 (2017). arXiv: 1708.01155. URL: http://arxiv.org/abs/1708.01155.

[18] Jiajun Wu et al. "Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling". In: *CoRR* abs/1610.07584 (2016). arXiv: 1610.07584. URL: http://arxiv.org/abs/1610.07584.

[19] Qiong Xu et al. "Low-dose X-ray CT reconstruction via dictionary learning". In: *IEEE Transactions on Medical Imaging* 31.9 (2012), pp. 1682–1697.