

Anatomy-Guided Synthesis of Novel CT Images at Full Hounsfield Range

Arjun Krishna

Computer Science Department
Stony Brook University
Stony Brook, NY, USA
arjkrishna@cs.stonybrook.edu

Ge Wang

Biomedical Imaging Center, School of Engineering
Rensselaer Polytechnic Institute
Troy, NY, USA
wangg6@rpi.edu

Klaus Mueller

Computer Science Department
Stony Brook University
Stony Brook, NY, USA
mueller@cs.stonybrook.edu

Abstract—In this work, we present an approach that can synthesize novel CT images across the full Hounsfield range using a very small annotated dataset of around thirty patients and a large non-annotated dataset with high resolution medical images. Our method uses these two datasets in a sequence of steps involving texture learning via StyleGAN and semi-supervised learning via CycleGAN to generate a large annotated medical dataset suitable for use in deep learning algorithms for medical applications. Using an anatomy exploration interface we can then generate CT images with anatomies that were non-existent within either of the datasets, without compromising accuracy and quality. We show that our approach works for all Hounsfield windows with minimal depreciation in anatomical plausibility.

Index Terms—medical imaging, GAN, deep learning, style loss

I. INTRODUCTION

Deep learning in medical applications is limited due to the low availability of large labeled, annotated or segmented training datasets. The scarcity in such datasets persists not only because of privacy and ownership concerns but also because of the high cost of labeling such datasets by human experts. Likewise, publicly available annotated high resolution image datasets are also often very small or even non-existent.

We present an approach to reduce or even eliminate the problem of such small datasets by converting them into large datasets without the loss of anatomical accuracy. Our approach goes beyond simple data augmentation techniques like stretching or flipping existing images and adds new data instances with anatomies that may not even exist in these datasets. With this approach we are able to increase not only the size but the overall diversity of images in datasets significantly.

We use a dataset of segmented CT images from thirty patients and a large dataset of unsegmented CT images. Our method builds on our previous work of texture learning [1] to expand the small annotated dataset with textures present in the large dataset. Subsequently we extract segmentation maps from the unsegmented large dataset via a trained U-Net. Next we train a cycleGAN on both the small segmented data and large unsegmented data in an alternate fashion to generate new images with segmentation maps as inputs. This synthesis step expands on our previous work [3] and explores the PCA space of segmentation maps in conjunction with the cycleGAN to create CT images with novel anatomies not present in either of the datasets.

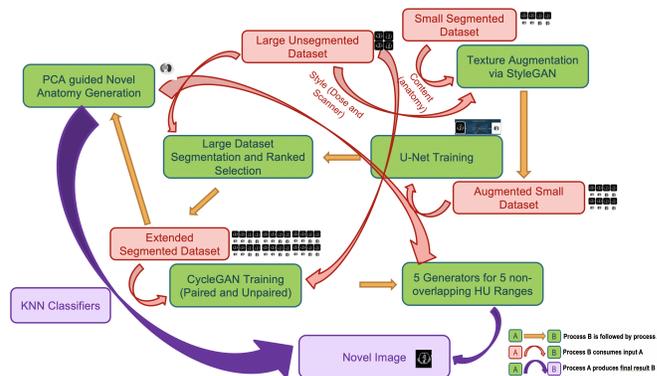


Fig. 1. Flow starts at the top right corner with two datasets - a small segmented and a large unsegmented dataset. Three different Deep-Learning networks are used starting from a StyleGAN followed by a U-NET segmentation network and 5 CycleGANs which train generators for the final step.

II. METHODS

Figure 1 highlights our sequence of steps. We will briefly summarize each step in the same sequence below.

A. Texture Augmentation

The smaller dataset consists of chest CT scans with segmentation maps (lungs, heart, etc.) of 30 patients. The larger dataset consists of non-annotated chest CT scans of $\sim 14k$ patients. To use the two datasets together we modified the textures of the smaller dataset with those of the larger one, augmenting the smaller annotated dataset 3-fold. We used the network architecture of [1] for segment-wise texture learning and created new CT images with the anatomy from the small dataset and the textures from the larger dataset.

B. Further Augmentation from Label Training

We train a U-Net [4] to output a segmentation map given a chest CT image as input. We use the augmented annotated dataset created in the previous step for training our U-Net. Having similar textures across the two different datasets helps in training a segmentation network on one dataset to segment the images of another. We use the trained U-Net to segment all 14k patient images. Since the smaller dataset has limited anatomy, there are errors in the segmentation outputs of the larger dataset. k-NN classifiers are used to rank them

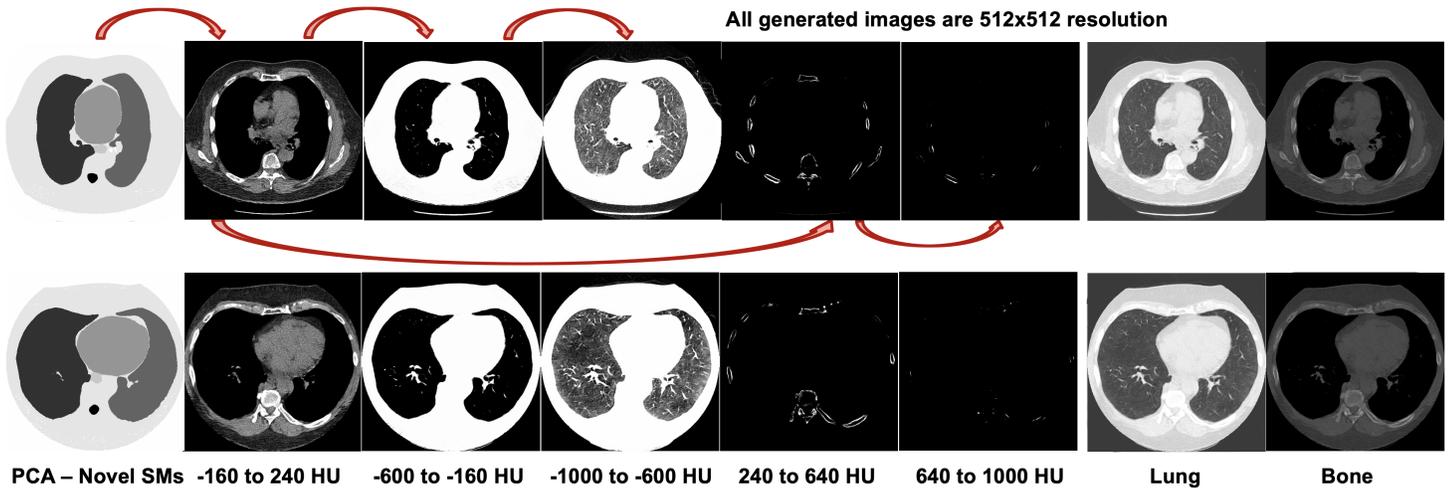


Fig. 2. Above figure shows two examples of novel ct scans generations. The sequential training and generation learns the correlations of anatomical details and could be clearly seen within the columns as we move from left to right. The last two columns depict the anatomical consistency observed in different HU windows than in generated ones. Each red arrow represents a generator of the two generators trained in a cycleGAN setup for corresponding modalities

by accuracy using certain characteristics of the segmentation images. We choose the best 1/4 of segmentation outputs and add them with their CT scans to the smaller segmented dataset. This dataset along with the larger dataset of unsegmented images is then used to train the generators for the synthesis.

C. Decomposing the Hounsfield Range for Generation Steps

Fig. 3a shows the average distribution of pixels values of a chest CT-scan over HU values. Fig. 3b shows an image in (-160, 240) HU range while Fig. 3c shows an image in (-600, -1000) HU ranges. Two separate generators are used to generate these HU ranges thereby assisting the GANs to focus on the minute details within these ranges since discriminators within a GAN setup focus on the accuracy of the majority group of pixels within a particular HU range. Hence we use five generators to generate five distinct sets of images for five distinct HU ranges for a single CT image generation. We first generate the middle HU range image using the segmentation map as input since it details the major anatomical features such as bones and organs. We then use this generated image as input for generating the other HU range images (Fig. 2).

D. Paired and Unpaired Training via CycleGAN

We follow the network architecture of [2] for paired and unpaired training. We use a different algorithm and data setup for training since our paired and unpaired datasets come

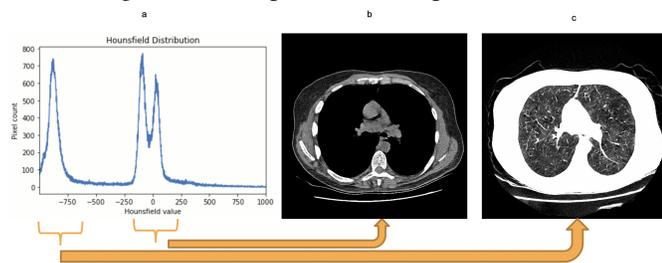


Fig. 3. We use 5 CycleGANs to train 5 generators for 5 non-overlapping HU ranges (-1000, -600), (-600, -160), (-160, 240), (240, 640), (640, 1000)

from different sources. We use only the large CT dataset for unpaired training while we use all the segmentation maps for both paired and unpaired training. Training was done in an alternate fashion; every iteration of paired training was followed by two iterations of unpaired training to learn the anatomical diversity present in the unsegmented dataset. As mentioned before, we have five such setups to produce five relevant generators to cover all five HU ranges.

E. Addition of Segmentation Maps via PCA

The larger dataset contains CT scans of around 14k patients while we have segmentation maps for only 3k patients. To balance the number of segmentation maps with CT-scans for training the cycleGAN we interpolate new segmentation maps in the PCA space of existing ones. For this we used our previous methodology [3] of representing segmentation maps as a set of B-Spline curves. Since interpolations may not be perfect anatomically we use k-NN classifiers to rank the validity of segmentation maps and chose the best ones as input for training the generators in paired/unpaired training in a cycleGAN [2] setup. The creation of new segmentation maps also helps in creating CT images with novel anatomy.

III. RESULTS

Fig. 2 shows the image synthesis sequence we use to cover the full HU-range. Shown are two CT images which exhibit novel anatomy. The left two columns demonstrate their anatomical consistency in the lung and bone windows.

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