Image Translation - MRI Images

Chinmayee Siddaramaiah, Graduate Student at USC
Instructor : Dr Anand Joshi

Abstract

MRI produces weighted images called T1 and T2. Each of this file in compressed format occupies a space of 7MB. T1 and T2 highlight areas in an inversion fashion though they are not inverse of each other. CycleGAN is a GAN which can translate unpaired images which are totally not related. It consists of two parts, generator and discriminator. Generator generates the translated version while discriminator checks on the correctness of the image translation through reconstruction. Using CycleGAN, we can translate T1 to T2 and vice-versa. Hence, using the T1 image we can get a T2 synthetic image. This translation is monitored by a loss function called cycle loss. Using the generated synthetic image, we obtain a reconstructed image, and the loss is calculated as the difference between the original image and the reconstructed image.

1 Introduction

Magnetic resonance imaging in short known as **MRI** is one amongst many tests performed in the field of neurosciences. MRI enables visualization of the brain anatomy in various planes : axial, sagittal and coronal. And hence, can contribute to detailed visualization of various regions like the brain, spinal cord and vascular anatomy.
There are different ways of storing scans, few being T1, T2 and flair. The concept behind the construction of these images is the repetition time and time to echo in short known as TR and TE.

	TR (msec)	**TE (msec)**
T1-Weighted (short TR and TE)	**500**	**14**
T2-Weighted (long TR and TE)	**4000**	**90**
Flair (very long TR and TE	**9000**	**114**

Figure 1 T1 and T2 in terms of TR and TE

In order to obtain T1 weighted images, a chemical called Gad is diffused. Amount of Gad changes the intensity of the signals, in case of T1 it shortens it resulting in brighter regions.
Some data and images related to T1 and T2 are shown in the figures below:

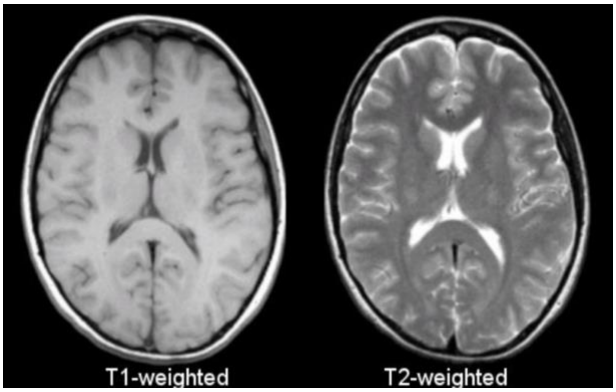

Figure 2 T1 and T2 images of brain

Tissue	T1-Weighted	T2-Weighted
CSF	Dark	Bright
White Matter	Light	Dark Gray
Cortex	Gray	Light Gray
Fat (within bone marrow)	Bright	Light
Inflammation (infection, demyelination)	Dark	Bright

Figure 3 Differences between T1 and T2 images of a brain

2 Image to image translation

Image to image translation refers to synthetic image generation involving certain modification in the synthetic image generated. For example, given an image of a dog, the translation must produce a synthetic image of a cat. To build a model to train data for image translation might be cumbersome as it involves collecting a huge dataset of “paired images”. At times this can be impossible.

2.1 CycleGAN

CycleGAN is a procedure or algorithm that can perform image translation without the need of paired data. It performs unsupervised training on input and target image collection which need not be related. Hence, cycleGAN can be used on unpaired data which are from unrelated domains. CycleGANs are used for season translation, change paintings to photographs, etc.

The way cycleGAN works is by learning the mapping between the two data which is done by the generator.

2.2 CycleGAN architecture

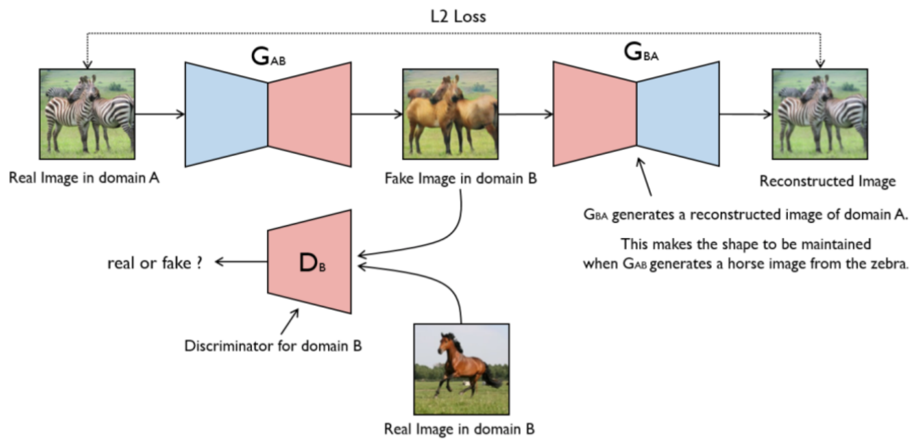

Figure 4 CycleGAN architecture from the original paper[4]

Generator is a block used to map the input from input domain (A) to output domain(B). In the case of there are two generator blocks used. One for generating domain A and one more for domain B. Convolutional neural networks are used in generator blocks. We have used resent.

Discriminator is an important block since it will check if the image synthesised matches the image from the output domain. In case of cycleGAN, there are two discriminator blocks, one to distinguish that generated from domain A and one more for domain B. Even in this block convolutional neural networks are used.

2.3 Loss

In case of normal GANs, discriminators are used as classifiers usually using sigmoid cross entropy as a loss function. In this case least square loss is used as the former likely ends up with vanishing gradients.

Discriminator

The loss that occurs in discriminator is based on whether the image synthesised is real or not. Mean squared error is used for error calculation. That is the output of the discriminator which can be 0/1 will be subtracted from whether it is real/not - 1/0, and the square of this error is measured.

Generator

This block produces images, whose correctness is evaluated by the discriminator and hence the loss for this block is evaluated in discriminator loss function. While on the other hand, apart from this adversarial loss, there is one more loss called cyclic loss which is calculated as the error between the reconstructed image of the synthetic image and the original image. This is called the "cycle consistency loss".

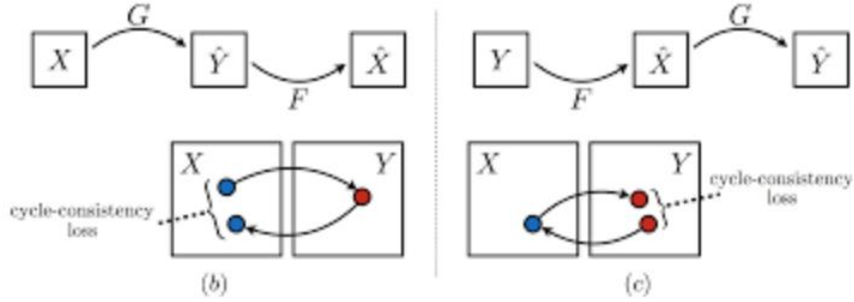

Figure 5 Loss

3 Code

The code involves reading of the data train and test data. There are two sets for train and test data. One set in each train test will be from T1 and one from T2. each of these images are in the nifti format. These images once read, will be trained. Based on the results obtained from training, testing is done on test data and performance evaluated.

3.1 Data reading

The input images are in nifti format. In order to read the images, nifti images were converted to numpy arrays. These images are stored as slices. In order to get one slice from each of the data, a slice stored at 55th location is used.

3.2 Training

Training involves training of both the generator and the discriminator and for each domain. In order to simplify the code, generic code will be written for generators and discriminators whose input will determine the domain that is being used.

Generators produce synthetic images. Using the first generator, T1 images are converted to T2 images. From the synthetic images of T2, reconstructed images of T1 are obtained using a second generator. Cyclic loss is found out. Discriminator is used to evaluate if this synthetic image of T2 is similar to that in the other domain that is T2 data. Loss is evaluated. Back propagation is carried out and optimization done.

The same steps as used in the case of T1 synthetic image generation. Various parameters like learning rate, batch size, number of epochs, weight decay parameters are changed and observed to get minimal loss.

4 Results

There were two sets of data that were used. One set had images in png format while the other had nifti format. Results of both are shown in the figure below. The convergence happened when 40 epochs were used. In case of nifti images, the data has different axes for the data and hence the orientation mismatch can be seen in the results. The results are in the form -

the first row has T1 and T2 original images, the second row has T2 and T1 synthetic images and the last row has reconstructed T1 and T2 images.

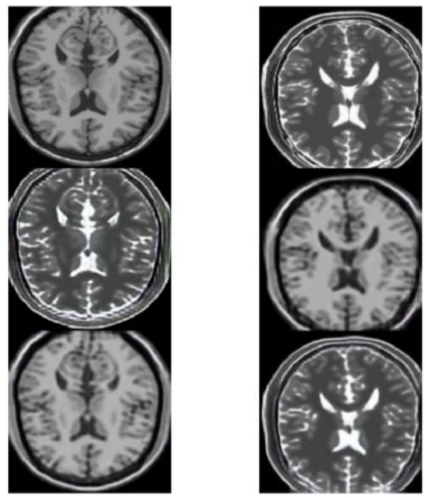

Figure 6 Results obtained using PNG format

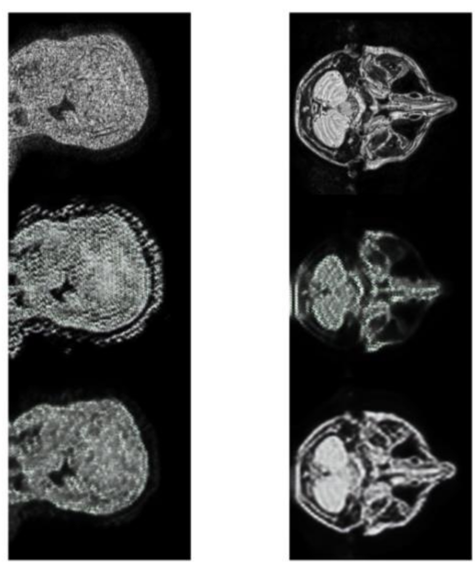

Figure 7 results obtained using nifti format

5. Conclusion and future work

From the cycleGAN architecture, we were able to successfully generate synthetic images of T1 and T2. In this work, only resnet has been used. And the loss function seemed to reduce with each epoch. The convergence took around 40 epochs. Generators usually start with very high error rates unlike discriminators. The discriminators tend to lower the error rates gradually almost by the end of 40 epochs that enables good synthetic image generation.

Future work involves trying to monitor the loss better and using better MRI data in nifti format that same axis across. Can try for different CNN configurations as well.

6 References and image sources

1. https://casemed.case.edu/clerkships/neurology/Web%20Neurorad/MRI%20Basics.htm
2. https://towardsdatascience.com/image-to-image-translation-using-cyclegan-model-d58cfff04755
3. https://arxiv.org/pdf/1703.10593.pdf
4. https://machinelearningmastery.com/what-is-cyclegan/