Semantic Image Synthesis with Generative Adversarial Networks of Brain MRI Images for Data Augmentation and Disentanglement

Israel Chaparro
Advisor: PhD. Javier Montoya

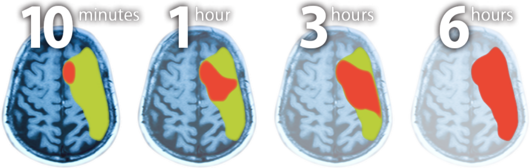
Department of Computer Science - UCSP

Summary

Motivation

Brain stroke was classified in 2016 as **2nd cause of death** according to the WHO [1], happens every **40 seconds** and every **4 minutes** someone dies from this disease.

Gliomas are the **most common primary brain neoplasms**, with various heterogeneous histological subregions (ED, NCR, ET, NET) described by **variable intensity profiles**. Due to this, the segmentation of brain tumors in multimodal MRI is one of the **most challenging tasks** in the area.



Motivation

Brain images are not easily available or are inconsistent; therefore, the **generation of synthetic images** would help to improve the automatic diagnosis.

A common goal in **disentanglement** is a latent space that consists of linear subspaces, each of which controls one factor of variation that represent **high-level attributes**.

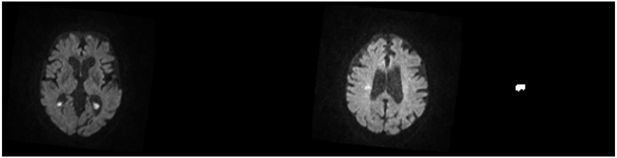


Figure: DWI of brain without and with stroke and the segmentation

Objectives

1. Review the state-of-the-art in Brain MRI Semantic Image Synthesis with GANs, and reproduce their results on existing datasets.
2. Develop a architectures for improve Synthesis and Segmentation of Brain Stroke Images using GANs.
3. Evaluate and validate the proposed architecture in different models and datasets to demonstrate the improvement.

Background - Related Works

1. A recent work in brain tumor image synthesis [2], evaluated in BraTS 2015, is based in pix2pixHD [3] adding a **Boundary-aware generator** in order to output the MR image and the boundaries of the complete tumor.
2. The state-of-the-art in unconditional image sythesis is the Style-based GAN (StyleGAN) [4] that uses **Adaptative Instance Normalization** and **intermediate** latent space.
3. The state-of-the-art in Semantic Image Synthesis [5] uses **SPatially Adaptive (DE)normalization** to effectively propagate the semantic information throughout the network.

Proposal: Deep Learning Model

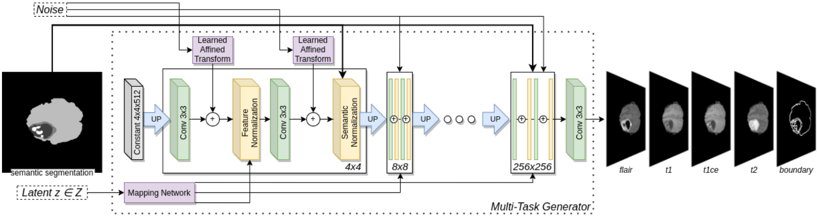


Figure: Generator Architecture Proposal

Image Synthesis: Basel Dataset

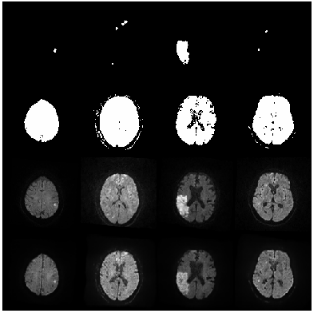


Figure: Stroke (1st row) Foreground (2nd row) Original (3rd row) Synthesis (4th row) in MR Images

Image Synthesis: Brats19

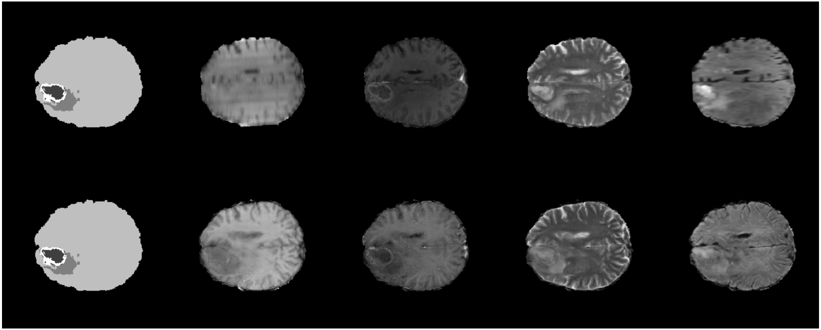


Figure: Original (1st row) Synthesis (2nd row) in MR Images

Video

Image Synthesis: Quantitative Results

Method	Dice			Precision			Sensibility		
	Cplt	Core	Enh.	Cplt	Core	Enh.	Cplt	Core	Enh.
wo/DA	0.78	0.54	0.43	0.85	0.79	**0.66**	0.78	0.47	0.37
w/DA	0.81	0.61	0.55	0.85	**0.82**	0.64	0.80	0.54	0.54
w/(our)DA	**0.84**	**0.63**	**0.57**	**0.87**	**0.82**	0.65	**0.84**	**0.57**	**0.54**

Performance on the BRATS19 testing

References

1 Walter Johnson et al. Stroke: a global response is needed, WHO.

2 Tony C.W Mok et al. Learning Data Augmentation for Brain Tumor Segmentation with Coarse-to-Fine Generative Adversarial Networks.

3 Ting-Chun Wang et al. High-Resolution Image Synthesis and Semantic Manipulation with Conditional GANs.

4 Karras, T. et al. A style-based generator architecture for GANs.

5 Park, T. et al. Semantic image synthesis with SPADE.

6 B. H. Menze et al. The Multimodal Brain Tumor Image Segmentation Benchmark.