CranGAN: Adversarial Point Cloud Reconstruction for patient-specific Cranial Implant Design

H. Sulakhe[1], J. Li[2], J. Egger[2], P. Goyal[1]

1 Birla Institute of Technology and Science, Pilani

2 Institute for AI in Medicine (IKIM), University Hospital Essen

INTRODUCTION

Cranioplasty is a surgical procedure to repair a bone defect in the skull due to a previous injury or an operation, such as a craniectomy. The procedure involves fitting a cranial implant in the region affected to replace the cranial bone. Prior to the surgery, careful designing of the cranial implant is a challenging and important task. The current method is to first obtain CT scans of the defected skull, convert them into a 3D mesh and then manually design the implant using CAD software which is expensive, not always accessible to clinical institutions and time-consuming. A flexible and computationally efficient process must be developed to resolve these issues in cranioplasty.

AIM

We present CranGAN - a 3D Conditional Generative Adversarial Network designed to reconstruct a 3D representation of a complete skull given its defective counterpart through point-cloud representations. We hope that our work inspires further research in this direction.

METHOD

CranGAN is formulated as an auto-encoder that processes 1024-point point clouds with an adversarial discriminator. The encoder is adapted from PointNet [1] and the decoder is a fully connected neural network. The discriminator is adapted from [2] and is 5-layer deep fully connected network. For optimization, 3D Reconstruction Losses - Hausdorff Loss and Chamfer Loss are employed.

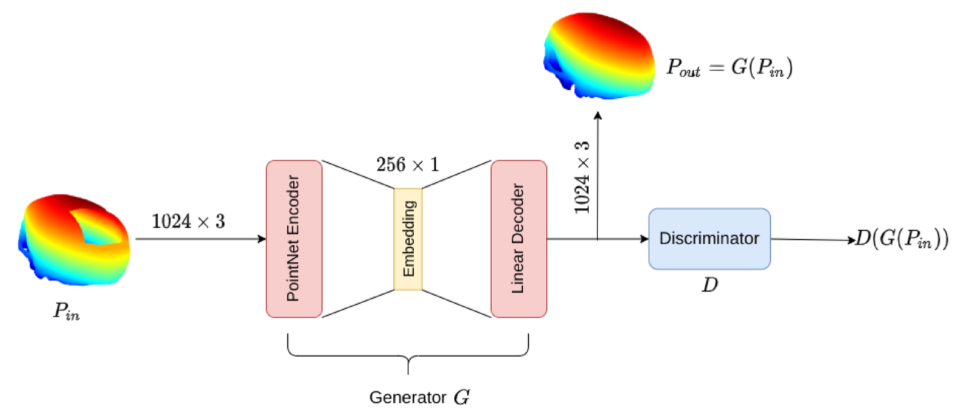


Illustration of the CranGAN architecture

RESULTS

A. Toy Experiments

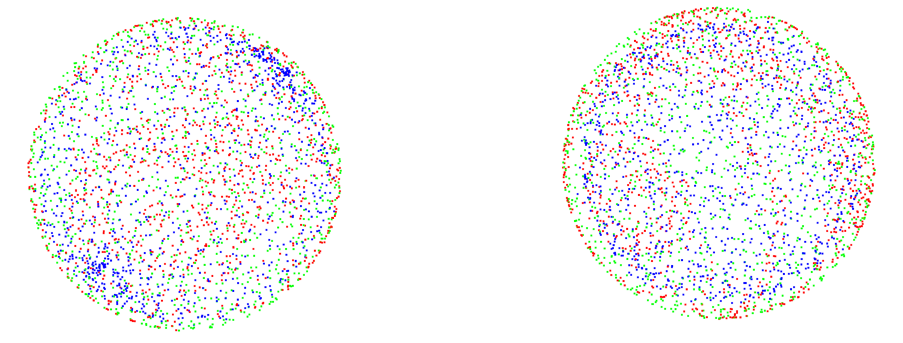
To ensure correctness of our approach, we first test our method on a toy dataset that is relatively less complex. A 2048-point point cloud of a sphere (of radius 1) is used and 1024-point point clouds are randomly sampled from it. In a similar setting to our main task, we expect the output to be a 1024-point point cloud in the shape of a complete sphere.

B. Main Experiments

We also provide multiple views of the results as an example for our main task. As an additional experiment, we also test our model on point clouds sampled purely from the ROI. In each of the figures, red points represent the input point cloud, green points represent the ground truth and blue points represent the output of the model.

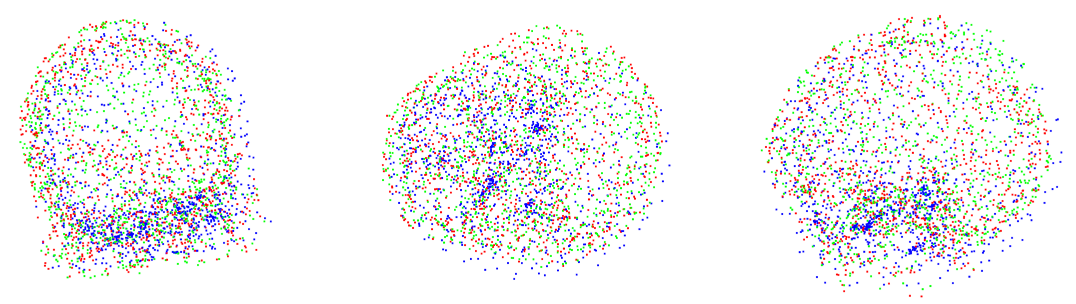
C. Outlier Removal and Surface Reconstruction

Since point cloud visualizations are relatively difficult to comprehend through 2D images, we try to provide better visualizations by reconstructing surfaces of the point clouds (output and ground truth). Prior to this, we perform a singular post-processing step of outlier removal on the synthesized point clouds. We then reconstruct surfaces from both the synthesized and ground truth point clouds for better visualization.



a) Chamfer Loss + Vanilla GAN b) Chamfer Loss + WGAN-GP

Figure A. Results of a few experiments on the toy dataset.



a) Front View b) Top View c) Side View

Figure B. Multiple views of the results on the skull data using Chamfer and Hausdorff Loss, with a Vanilla GAN setting.

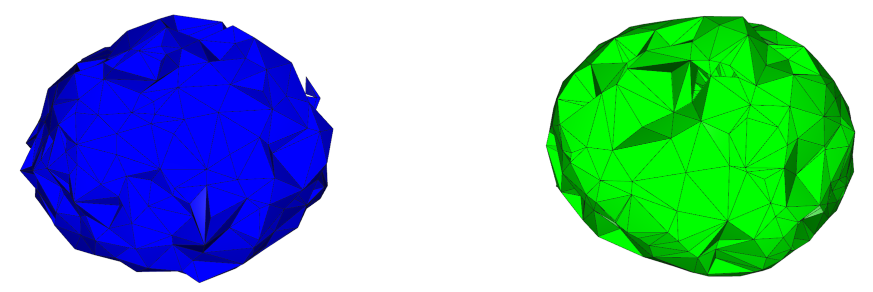


Figure C. Surface reconstructions of point clouds from an example data point. Blue - prediction, Green - ground truth.

GAN Objective	Hausdorff Loss	Chamfer Loss	Hausdorff Distance	Chamfer Distance
Vanilla	✓	-	1.504	0.915
	-	✓	1.307	0.644
	✓	✓	1.488	0.716
WGAN-GP	✓	-	1.537	0.709
	-	✓	**1.219**	0.696
	✓	✓	1.420	0.901
LSGAN	✓	-	1.520	0.695
	-	✓	1.241	**0.564**
	✓	✓	1.472	0.715

TABLE I: Results of CranGAN on the toy dataset.

GAN Objective	Hausdorff Loss	Chamfer Loss	Hausdorff Distance	Chamfer Distance
Vanilla	✓	-	**25.477**	**12.113**
	-	✓	43.911	25.257
	✓	✓	48.483	25.532
WGAN-GP	✓	-	42.994	23.752
	-	✓	26.525	12.504
	✓	✓	30.333	13.063
LSGAN	✓	-	27.357	12.313
	-	✓	248.321	177.559
	✓	✓	35.643	18.350

TABLE II: Results of CranGAN on the main experiments.

CONCLUSIONS

This paper presents a 3D GAN network for cranial implant design. We utilize point cloud representations and demonstrate the effect of utilizing two 3D reconstruction losses while experimenting with three GAN objectives. We believe this work will inspire further research in this domain and consequently provide for an accurate and efficient approach to automatizing cranial implant design for biomedical purposes [3]. Finally, we plan to add CranGAN to StudierFenster (www.studierfenster.at) in the future, to provide an end-user friendly version to the community.

REFERENCES

[1] **Charles R. Qi, Hao Su, Kaichun Mo, and Leonidas J. Guibas.** Pointnet: Deep learning on point sets for 3d classification and segmentation. *In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), July 2017.*

[2] **Chun-Liang Li, Manzil Zaheer, Yang Zhang, Barnabas Poczos, and Ruslan Salakhutdinov.** Point cloud gan. *arXiv preprint arXiv:1810.05795, 2018.*

[3] **Jianning Li, Gord von Campe, Antonio Pepe, Christina Gsaxner, Enpeng Wang, Xiaojun Chen, Ulrike Zefferer, Martin Toedtling, Marcell Krall, Hannes Deutschmann, et al**. Automatic skull defect restoration and cranial implant generation for cranioplasty. *Medical Image Analysis, 2021.*

ACKNOWLEDGEMENTS

We acknowledge CAMed (COMET K-Project 871132), enFaced (KLI 678), enFaced 2.0 (KLI 1044) and KITE (Plattform fur KI-Translation Essen) from the REACT-EU initiative (https://kite.ikim.nrw/)

CONTACT INFORMATION

Harsh Sulakhe – f20180186@pilani.bits-pilani.ac.in

Jianning Li – jianning.li@uk-essen.de

Jan Egger – jan.egger@uk-essen.de

Poonam Goyal – poonam@pilani.bits-pilani.ac.in