Learning Volumetric Shape Super-Resolution for Cranial Implant Design

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INTRODUCTION

Cranioplasty is the process of repairing cranial defects or deformations. The aim of this procedure is to re-establish the aesthetic shape of the head and to protect the brain from further injuries. Shaping the needed cranial implant is often a costly and time-consuming work [1]. Inspired by the development of a web-based fully automated cranial implant design pipeline by Li et al. [2], this study aims to explore a way to ease the implant generation task.

METHOD

We use a deep learning approach and split the implant generation into three stages. First, a convolutional neural network is used to reconstruct the skull at low resolution, then we use a second network to up-sample the result to high resolution. Finally the implant is generated by simple subtraction and filtering.

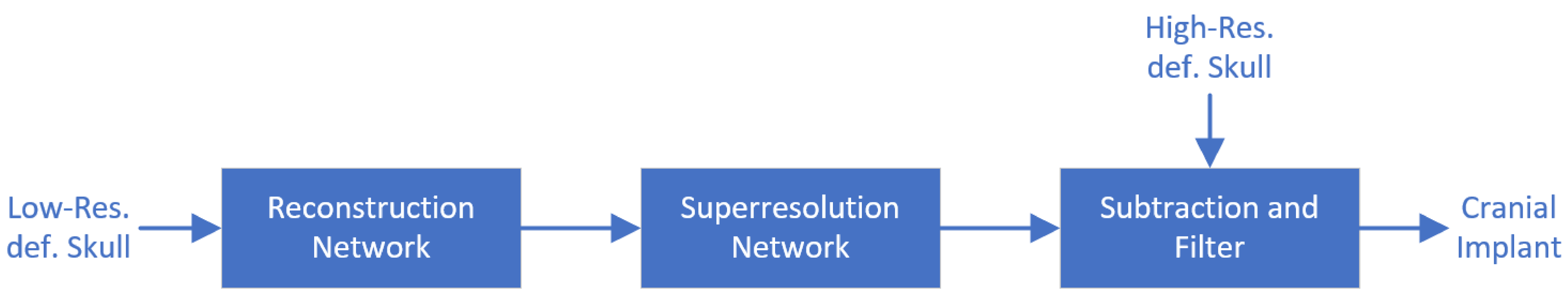

Figure 1 – Implant generation pipeline.

RECONSTRUCTION

The skull reconstruction is conducted on data with a resolution of 30x30x30. For this task, a network with a U-Net [3] shape was chosen. The encoder/decoder path of the U-Net captured the shape of the human skull, while the skip connection preserved the preexisting details of the input data.

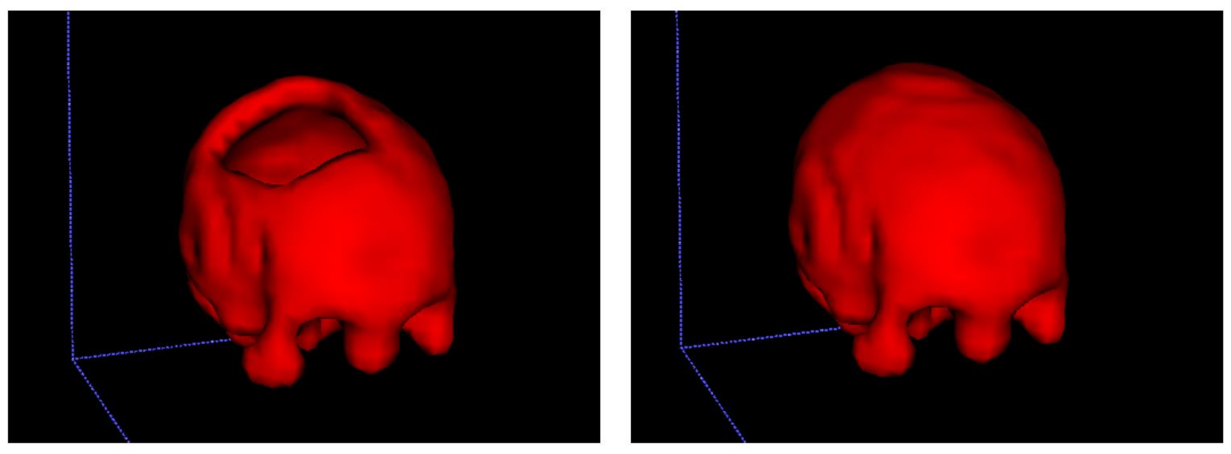

Figure 2 – Input data with cranial defect (left), reconstruction-network output (right).

SUPER-RESOLUTION

The super-resolution network lifted the skull resolution from 30x30x30 to 60x60x60. Again a U-Net shape was chosen for this task. The decoder path utilized the pixel-shuffle technique [4] to increase the voxel count. For comparison, the super-resolution was also conducted via cubic interpolation.

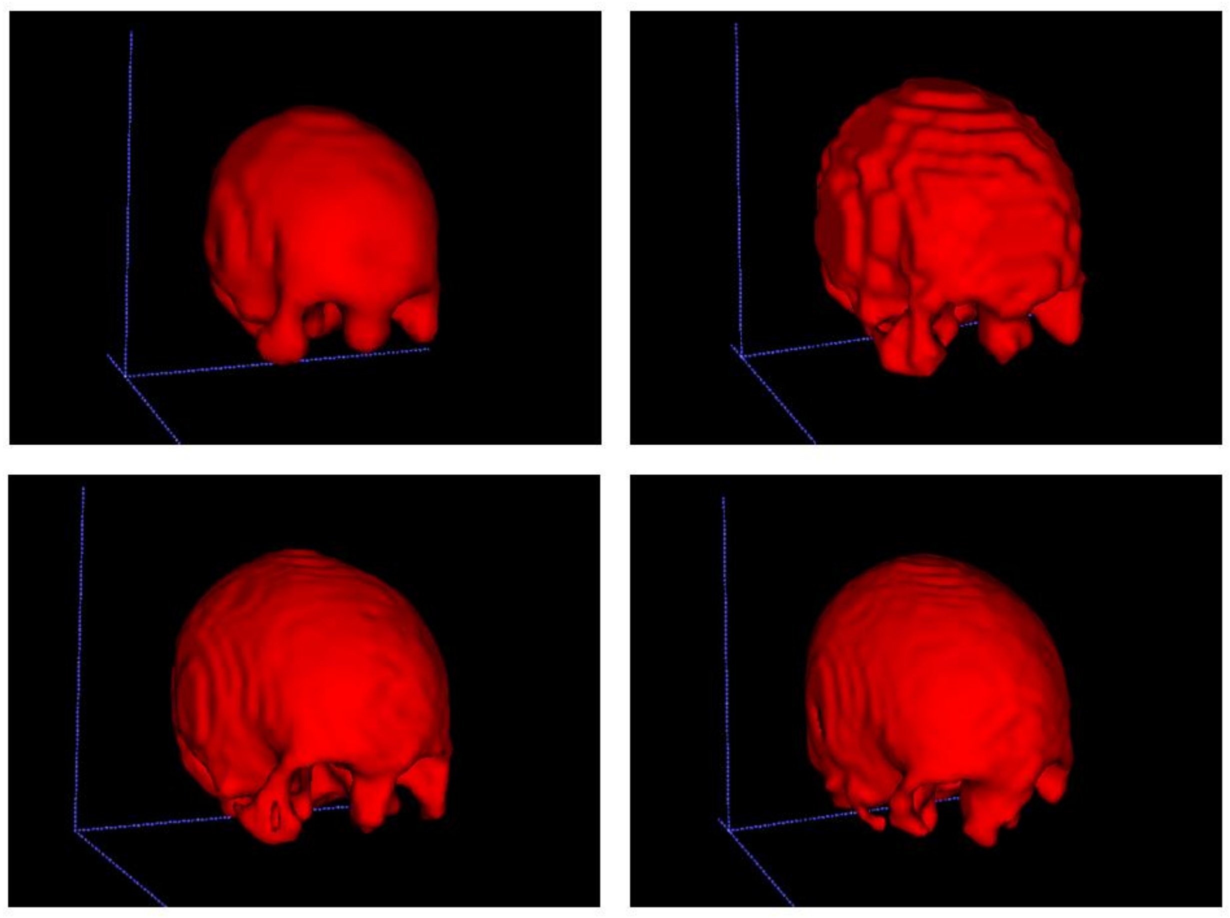

Figure 3 – Low-resolution input (top left), cubic interpolation output (top right), high-resolution target (bottom left), SR-network output (bottom right).

EXPERIMENTS AND RESULTS

The performance of the networks was evaluated on a dataset provided by Morais et al. [5]. It contains 222 examples of healthy and defect skulls with resolutions ranging from 30x30x30 to 128x128x128. The Sørensen-Dice Index was used to compare the results.

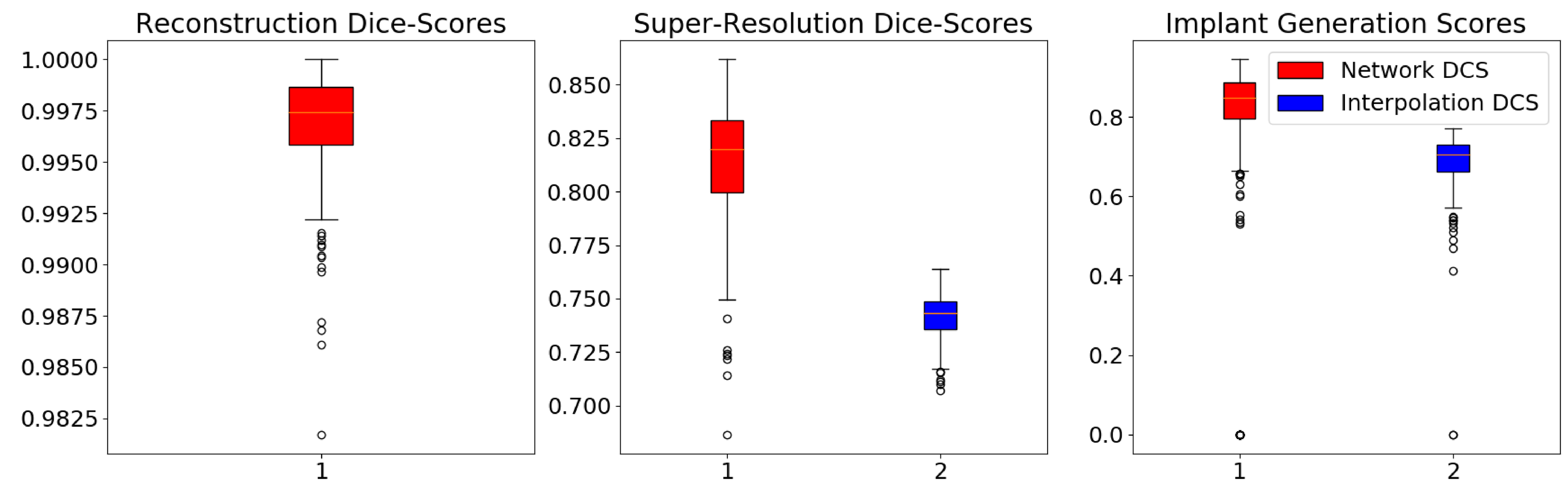

Figure 4 – Dice-Score distribution for reconstruction (left), super-resolution (middle) and implant generation (right).

	Rec (s)	Super-res (s)	Cubic interp (s)	Super-res (imp)	Cubic interp (imp)
Average	0.9967	0.8128	0.7418	0.8337	0.6883
Min	0.9817	0.6865	0.7069	0.5307	0.4132
Max	1.0	0.8619	0.7639	0.9452	0.7705

Table 1 – DSC of the skull (s) and implant (imp).

DISCUSSION AND CONCLUSION

The reconstruction network delivered good results on data with 30x30x30 resolution. The skulls were reconstructed without adding unwanted additional structures. In contrast, while the super-resolution network delivered very natural looking results in comparison to a cubic up-sampling stage, it suffered from random blobs which were added to the skull. This happened especially when the input data differed from usual samples, e.g. when the skull was deformed or included artifacts.

These hallucinations turned out to be a problem for the final stage, where they lead to problems with the automatic implant generation. While the network hit higher scores compared to the cubic interpolation variant, there is still room for improvement of the hallucination suppression. Either by changing the super-resolution network or the blob-filtering algorithm. In summary, the project showed the potential to create a new and efficient way for automatic cranial implant generation and gave an entry point for future work on higher resolutions.

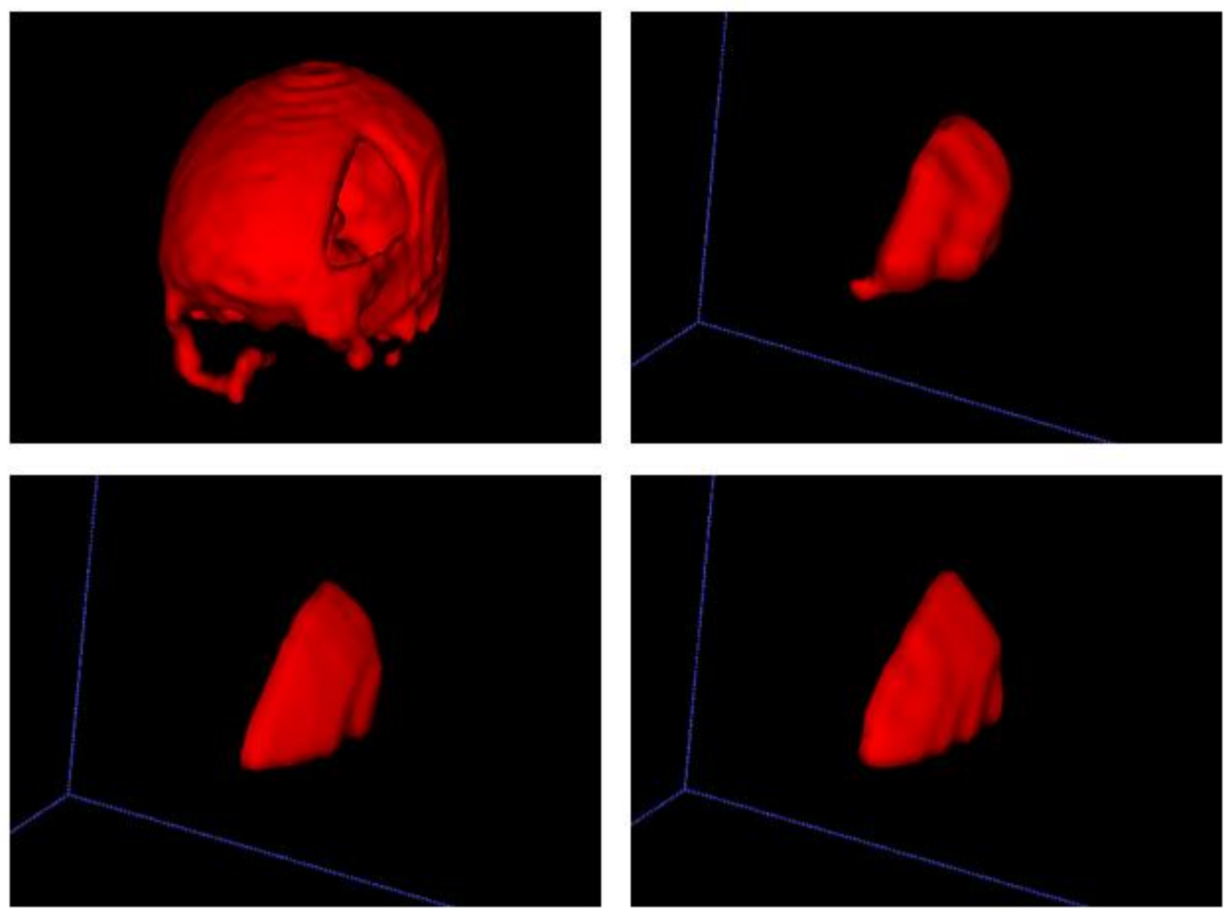

Figure 5 – Defect high-res skull (top left), cubic interpolated implant (top right), super-resolution implant (bottom left), ground truth (bottom right)

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