High-resolution Cranial Implant Prediction via Patch-wise Training.

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Introduction

A cranial defect usually occurs after injury, tumor invasion or infection. The current process of cranial implant design and manufacturing usually involves costly commercial software and highly-trained professional users [1]. An automatic, low-cost design and manufacturing of cranial implants can bring significant benefits and improvements to the current clinical workflow for cranioplasty [2].
The AutoImplant Challenge [3] is organized in order to tackle the problem of automatic cranial implant design in a data-driven manner, without relying explicitly on geometric shape priors of human skulls [4]. The organizers provide 3D binary images of defective skulls, complete skulls and implants as the datasets, with which the reconstruction of implants can be proceeded either directly from defective skulls, or from the differences between defective and complete skulls.

Method

We examined mainly two methods based on the deep learning model structure V-Net [5], which are the resize method and the patch-based method.

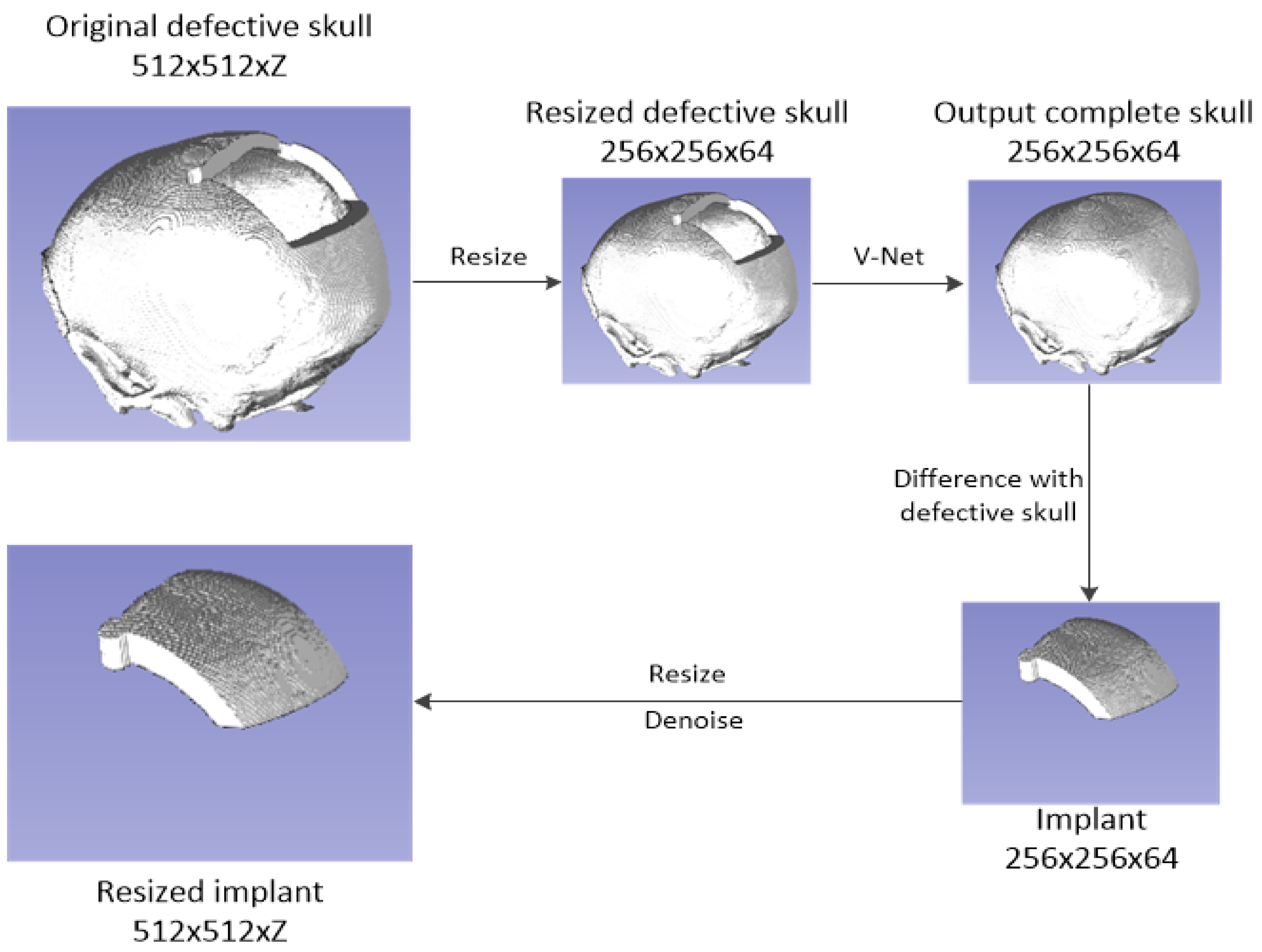


Figure 1 – Workflow of resize method. The original defective skulls are resized to 256x256x64 and then inputted into the network. The implants are obtained via the difference of the outputted complete skulls and the inputted defective skulls. Finally the implants are resized back to the original sizes and then denoised to improve the prediction accuracy.

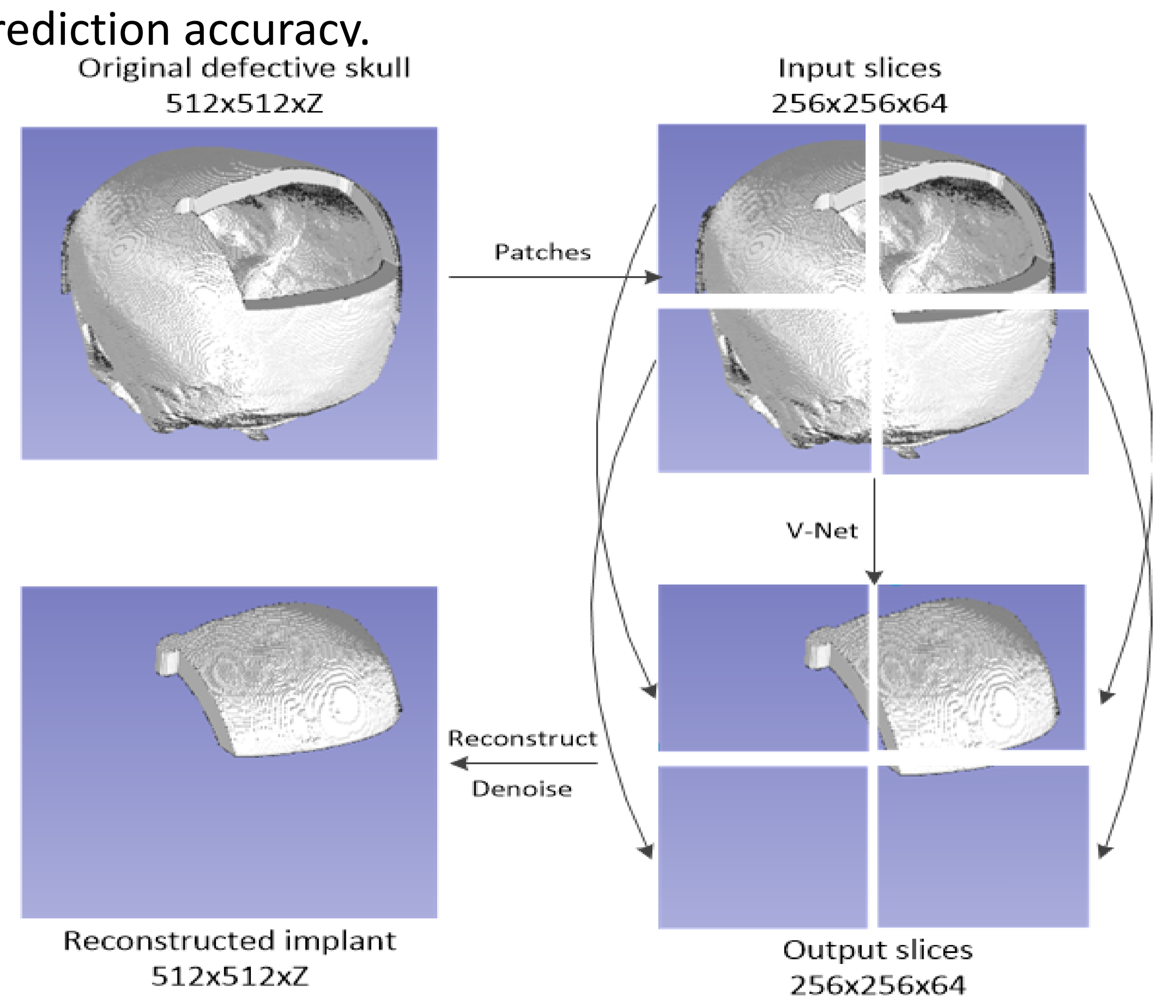


Figure 2 - Workflow of patch-based method. The original defective skulls are split into slices with constant patch shape of $256\times 256\times 64$ and stride shape of $128\times 128\times 32$. For example, an original image with the size of $512\times 512\times 256$ is split into 63 slices ($[0,256]^2[0,64]$, $[0,256]^2[32,96]$, $[0,256]^2[64,128]$,...). All the slices are inputted into the network separately and the resulted slices are combined to reconstruct the implants.

EXPERIMENTS AND RESULTS

We evaluated our two methods with the 100 test images from Autoimplant Challenge, in which the dice similarity score (DSC) and Hausdorff distance (HD) are used as the evaluation metrics.

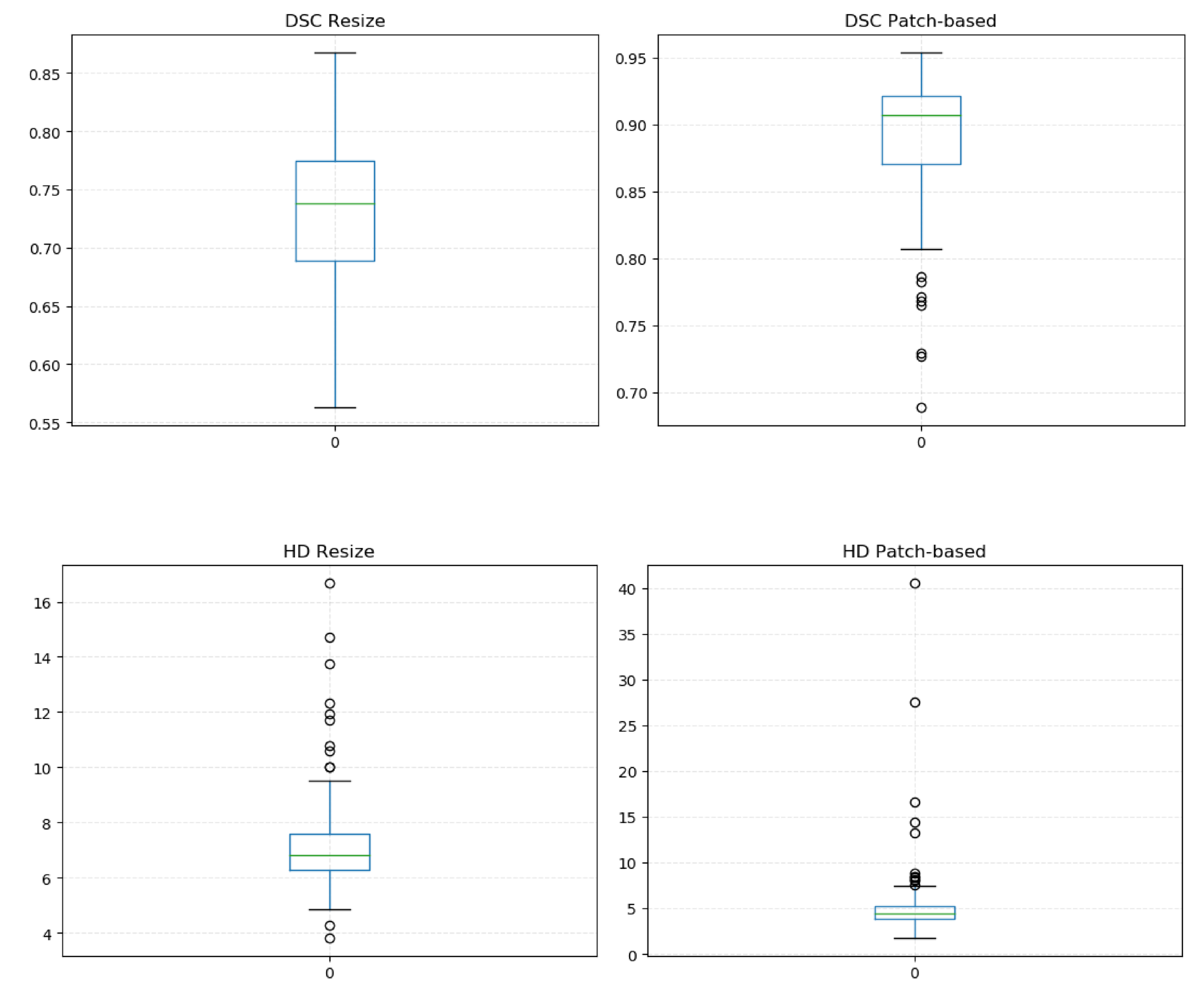


Figure 3 – DSC and HD boxplots of the 100 test cases with resize (left) and patch-based (right) methods.

Table 1 – Mean values of DSC and HD for resize and patch-based methods.

	DSC	HD (mm)
Resize	0.7350	7.2425
Patch	0.8887	5.5339

DISCUSSION AND CONCLUSION

Due to the computational limitation of training the state-of-the-art networks using GPU, we were not able to input the whole skull volume of size 512x512xZ to a neural network for training. To overcome this problem, we developed and applied two methods: a resize method and a patch-based method. The former one changes directly the sizes of the original images and inputs them into the neural network, while the latter one inputs part of the original images to train the network.
Based on the comparison of the testing, even with the same model structure and training process, the final results with the patch-based method is much better than the results of the resize method. Hence, it can be concluded that a simple resize algorithm can lead to big degradation in the accuracy of images, which is much worse than the problems that occur with the patch-based method. A qualitative comparison between the results of resize method and patch based method is shown in Figure 4.

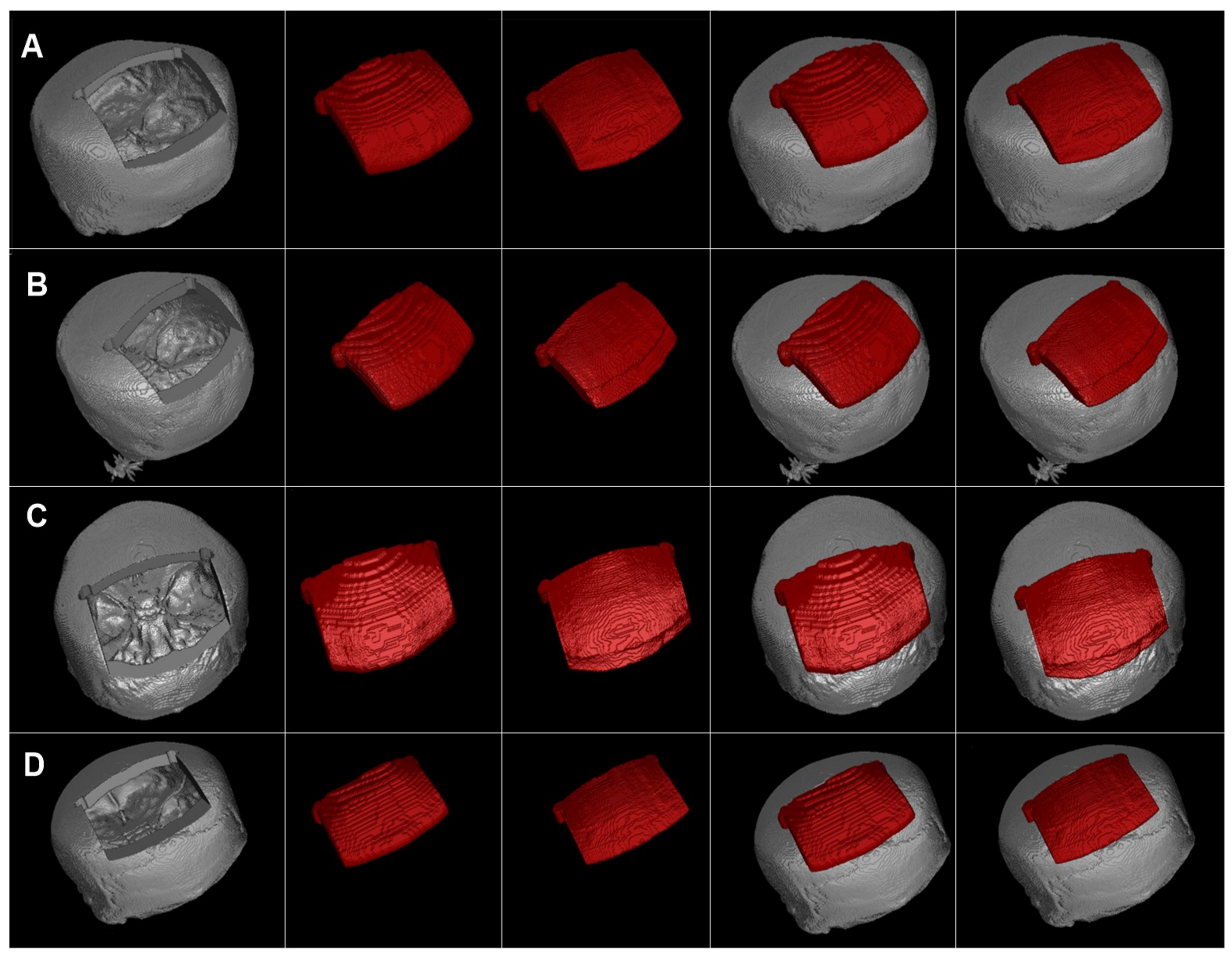
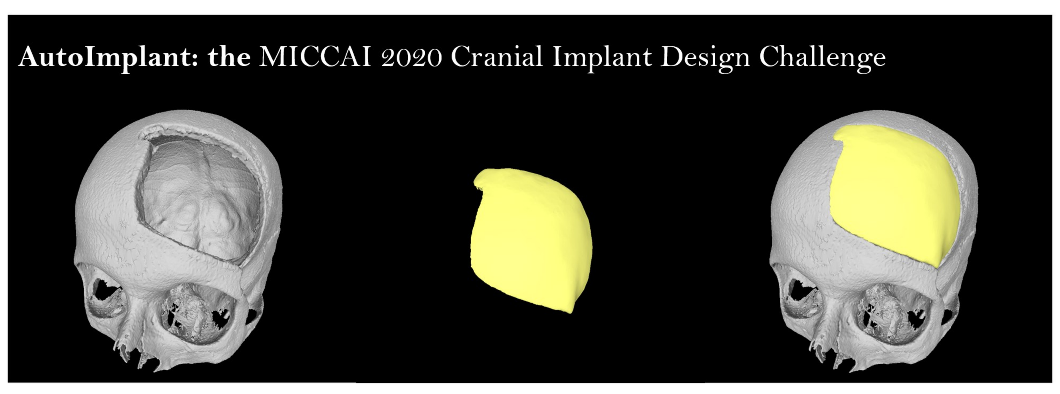


Figure 4 – (A)-(D) implant prediction results on four images from the test dataset. From left to right: the input defective skulls; the predicted implants with resize method; the predicted implants with patch-based method; overlay of the implants from resize method (fourth column) and patch-based method (fifth column) on the defective skulls. Different colors are used for the implants (red) and skulls (gray).

REFERENCES

1. Digital evolution of cranial surgery. A case study by renishaw plc in new mills, Wotton-under-Edge Gloucestershire, GL12 8JR United Kingdom (2017)
2. Long, J., Shelhamer, E., Darrell, T.: Fully convolutional networks for semantic segmentation. CoRR abs/1411.4038 (2014), http://arxiv.org/abs/1411.4038
3. Li, J., Egger, J.: Towards the automatization of cranial implant design for 3d printing (2019). https://doi.org/10.13140/RG.2.2.16144.56324
4. Li, J., Pepe, A., Gsaxner, C., Campe, G., Egger, J.: A baseline approach for autoimplant: the miccai 2020 cranial implant design challenge (2020)
5. Milletari, F., Navab, N., Ahmadi, S.: V-net: Fully convolutional neural networks for volumetric medical image segmentation. CoRR (2016), http://arxiv.org/abs/1606.04797



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