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CT image segmentation for additive manufactured skull implants using deep learning

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Abstract: A major challenge in attaining customized additive manufactured (AM) skull implants is segmentation of computed tomography (CT) scans. Therefore, this study aimed to develop a deep learning algorithm, specifically a mixed-scale convolutional neural network (MSDnet), to automatically segment skull defects in CT scans. The MSDnet was trained with CT scans and corresponding virtual 3D models of patients who had undergone cranioplasty using AM skull implants. The trained MSDnet segmented unseen CT scans accurately and quickly. Deep learning can thus remove the barriers of time and effort during CT image segmentation, thereby making customized AM skull implants more accessible to clinicians.

I. Introduction

Additive manufacturing (AM) is causing a paradigm shift in medicine away from one-size-fits-all to personalised treatments. AM has proven to be particularly valuable in the field of cranio-maxillofacial surgery since it offers the opportunity to fabricate customized constructs such as skull implants [1]. The current process of creating such customized implants comprises three steps: 1) acquiring 3D images of the patient using computed tomography (CT); 2) image processing, in which the CT images are converted into a virtual 3D surface model that can be used to design the implant; and 3) manufacturing the implant using a 3D printer.

The most important step in the conversion of CT images into a virtual 3D model (step 2) is image segmentation: the partitioning of images into regions of interest that correspond to a specific anatomical structure (e.g., bone). However, common image segmentation methods used for medical AM cannot deal with noise, artefacts and intensity variations in images [2,3] hence extensive and time-consuming manual post-processing of virtual 3D models is often required. Therefore, new methods to automate image segmentation are sought.

Over the past few years, there have been unparalleled advances in using deep learning for a wide variety of image processing tasks. In particular, convolutional neural networks are becoming the standard for medical image segmentation [4]. Therefore, the aim of this study was to develop and train a neural network to segment skull defects in CT scans for medical AM.

II. Material and methods

In this study, we used a mixed-scale dense convolutional neural network architecture (MSDnet) originally proposed by Pelt and Sethian [5] that combines small- and large-scale features with far fewer trainable parameters compared with state-of-the-art U-Net architectures [6]. The MSDnet was trained using 15 CT scans (512 x 512 and a variable number of slices) and corresponding virtual 3D models of patients who had previously undergone craniotomy and cranioplasty using customized AM skull implants. The aforementioned virtual 3D models had been created by experienced medical engineers and served as the “gold standard” in this study. All virtual 3D models were first aligned with their corresponding CT scans and subsequently converted into gold standard labels using the mesh-to-label conversion module in 3D Slicer software (v.4.6.3) [7].

MSDnet training was performed on an HP Workstation Z840 with 64 GB RAM, an Intel Xeon E5-2687 v4 3.0GHZ CPU, and an NVIDIA GTX 1080 Ti GPU card. The MSDnet implementation was performed in PyTorch (v.0.4.1) and is publicly available online [8]. Training took approximately 1 h (10 epochs) and the segmentation of one CT scan took approximately 20 s. The MSDnet performance was evaluated using five CT scans and corresponding gold standard virtual 3D models that were not used for training. The quality of the resulting MSDnet segmentations was assessed using the Dice similarity coefficient (DSC):

$$DSC = \frac{2TP}{2TP+FP+FN}, \tag{1}$$

where TP is the number of true positives, FP is the number of false positives, and FN is the number of false negatives. In addition, all five CT scans segmented by the MSDnet were converted into virtual 3D surface models

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and geometrically compared to the original gold standard models created by the medical engineers.

III. Results and discussion

The five CT scans segmented using the trained MSDnet demonstrated a high overlap with the gold standard segmentations (Fig. 1), with a mean DSC of 0.96 ± 0.02 (Table 1). Note that this DSC is higher than the DSCs achieved by traditional segmentation methods such as level-set methods [9], atlas-based methods [10] and prior-guided random forests [11]. Furthermore, the resulting MSDnet-based virtual 3D models were of high quality (Fig. 2) with an MAD of 0.33 mm ± 0.16 mm (Table 1). Interestingly, the virtual 3D models obtained using the MSDnet were more accurate in the proximity of the skull defects with an MAD of 0.19 mm ± 0.14 mm (Table 1). This difference could have been caused by the medical engineer, who manually removed all noise residuals and smoothened the defect edges of the gold standard virtual 3D models to ensure the best fit of the customized AM skull implants. Since these gold standard virtual 3D models were used to generate training data, the MSDnet learned to reproduce these smooth and accurate defect edges in its segmentation process. These results demonstrate that virtual 3D models created by medical engineers can thus provide new avenues to generate high-quality training data for deep learning algorithms.

In conclusion, deep learning offers the opportunity of removing the prohibitive barriers of time and effort during CT image segmentation in the medical AM workflow, thereby making customized AM constructs such as skull implants more affordable, and thus more accessible to clinicians.

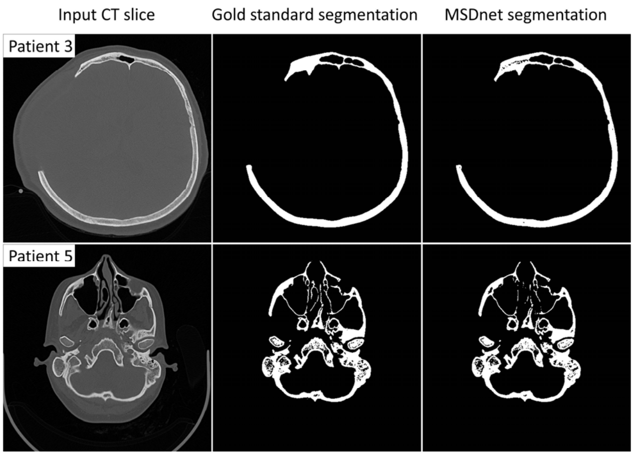

Figure 1: CT slice, gold standard segmentation, and MSDnet segmentation of patients 3 and 5.

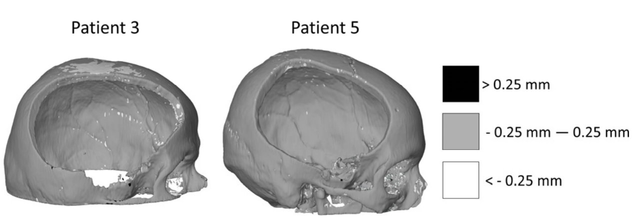

Figure 2: Virtual 3D models acquired using the MSDnet of patients 3 and 5.

Table 1: Dice similarity coefficient (DSC) between the gold standard and the MSDnet segmentations, and the mean absolute deviations (MADs) between the gold standard and the MSDnet-based virtual 3D models. MADs were calculated of the full skull, as well as in the area near the skull defect.

Patient ID	DSC	MAD of full skull (mm)	MAD of defect area (mm)
1	0.93	0.48	0.37
2	0.98	0.30	0.08
3	0.96	0.47	0.33
4	0.99	0.09	0.09
5	0.96	0.34	0.10
Mean	**0.96 ± 0.02**	**0.33 ± 0.16**	**0.19 ± 0.14**

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References

[1] A. L. Jardini *et al.*, "Cranial reconstruction: 3D biomodel and custom-built implant created using additive manufacturing," *Journal of Cranio-Maxillofacial Surgery*, vol. 42, no. 8, pp. 1877–1884, Dec. 2014.

[2] M. van Eijnatten, R. van Dijk, J. Dobbe, G. Streekstra, J. Koivisto, and J. Wolff, "CT image segmentation methods for bone used in medical additive manufacturing," *Medical Engineering & Physics*, vol. 51, pp. 6–16, Jan. 2018.

[3] N. Sharma and L. M. Aggarwal, "Automated medical image segmentation techniques.," *Journal of medical physics / Association of Medical Physicists of India*, vol. 35, no. 1, pp. 3–14, 2010.

[4] G. Litjens *et al.*, *A survey on deep learning in medical image analysis*, vol. 42. 2017.

[5] D. M. Pelt and J. A. Sethian, "A mixed-scale dense convolutional neural network for image analysis," *Proceedings of the National Academy of Sciences*, vol. 115, no. 2, pp. 254–259, Jan. 2018.

[6] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015*, pp. 234–241, 2015.

[7] A. Fedorov *et al.*, "3D Slicer as an image computing platform for the Quantitative Imaging Network," *Magnetic Resonance Imaging*, vol. 30, no. 9, pp. 1323–1341, 2012.

[8] A. Hendriksen, *msd_pytorch*. Github, 2019.

[9] N. Torosdagli *et al.*, "Robust and fully automated segmentation of mandible from CT scans," in *2017 IEEE 14th International Symposium on Biomedical Imaging (ISBI 2017)*, Melbourne, Australia, 2017, pp. 1209–1212.

[10] K. A. Powell, T. Liang, B. Hittle, D. Stredney, T. Kerwin, and G. J. Wiet, "Atlas-Based Segmentation of Temporal Bone Anatomy," *International Journal of Computer Assisted Radiology and Surgery*, vol. 12, no. 11, pp. 1937–1944, Nov. 2017.

[11] L. Wang *et al.*, "Automated segmentation of dental CBCT image with prior-guided sequential random forests: Automated segmentation of dental CBCT image," *Medical Physics*, vol. 43, no. 1, pp. 336–346, Dec. 2015.