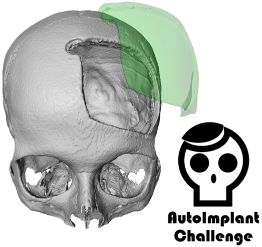

006_AutoImplant: the MICCAI 2020 (2021) Challenge on Cranial Implant Design

Joint DL and BIA Final Project

Mariya Donskova & Aleksandr Nevarko & Alexey Shevtsov & Konstantin Soshin & Anita Soloveva

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Introduction

Task

Cranioplasty — the surgical process where a skull defect is repaired using a cranial implant.

Main problem

Automatically design such an implant so that it fits precisely against the borders of the skull defect as a replacement to the removed cranial bone.

Biomedical Literature Review

- Access to Investigational Brain Implants: (Lázaro-Muñoz et al. 2018)
- Brain Implants With Computing Devices: (Křemen et al. 2018; Baldassano et al. 2018)

Introduction

Dataset (Kodym et al. 2021)

114 aligned 3D binary skull masks of size 512^3.

Corresponding pairs with artificially generated defects in bilateral, frontoorbital, parietotemporal and random regions.

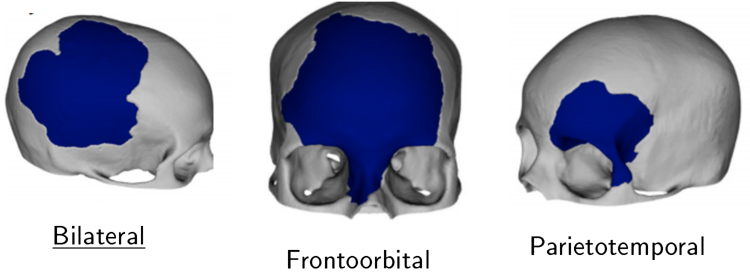


Figure: Examples of possible implant localization.

Introduction

Imaging Modality: CT

- More appropriate for processing bone structures in comparison with MRI
- Less publicly available CT datasets

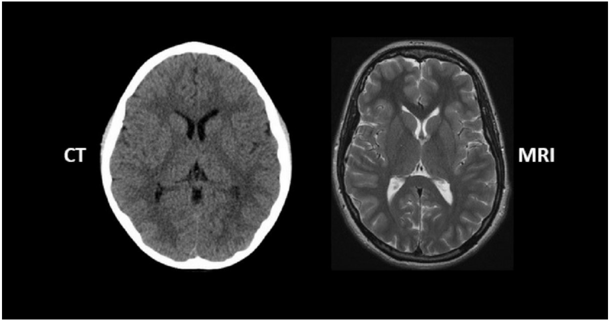
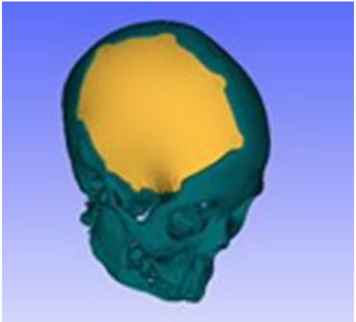


Figure: Examples of head CT and MRI slice.

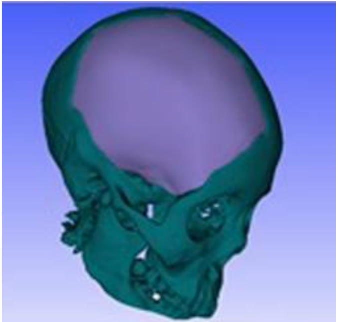
Introduction

Tools & Models

- Computer-Aided Design (CAD) Softwares (Egger et al. 2017) that are user-dependent and time-consuming
- 3D encoder-decoder for MRI data: (Morais et al. 2019)
- Autoimplant 2020 papers: (Li & Egger 2020)



Implant designed using traditional softwares



Implant designed using EasyCrania (CAD Software)

Presentation Overview

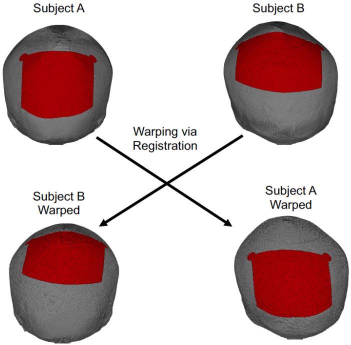
- Dataset Expansion
- Baseline Solutions
- SAU-Net
- 3D U-Net
- Metrics & Results
- Visualisation
- Conclusions

Github Repo: Autoimplant-2020-2021

Dataset Expansion

Two techniques:

- Spherical and cubic defects of various size and localization extraction from the complete skulls to match with standard surgeries (in the lower part a craniectomy cannot occur) (Li et al. 2020; Matzkin et al. 2020)
- Automatic co-registration between the given skull masks (Ellis & Aizenberg 2020)



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Baseline: One-stage (Morais et al. 2019)

Autoencoder that generates a complete, but low-resolution skull as an output, which is then correlated with shape priors to generate a high resolution output. Experiments with 3 different resolutions: 30^3, 60^3 and 120^3.

Resolution	Input / Output / Ground-truth	Error
30^3		2.394%
60^3		2.471%
120^3		3.515%

Figure: Examples of autoencoder output for different resolutions.

Baseline: Two-stage (Li et al. 2020)

Two-stage model:

1. First autoencoder learns a coarse implant representation from down-sampled skull to localize the bounded area for the defected region in the original resolution.
2. Second autoencoder generates a fine-tuned implant for the extracted region.

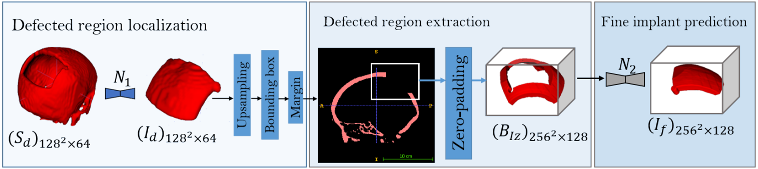

Figure: Two-stage model scheme

Autoimplant 2020 1st place: 3D U-Net (Ellis & Aizenberg 2020)

Two experiments:

- With 3 layers
- With full depth as in the paper

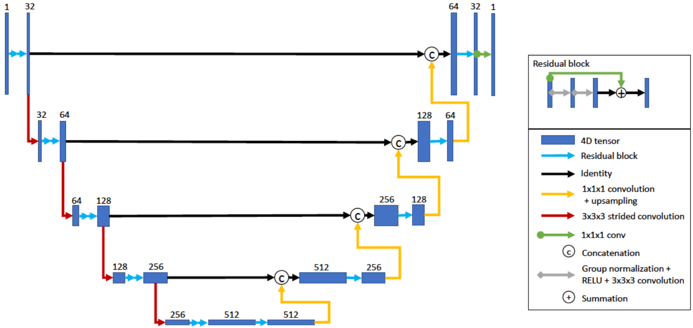

Figure: Autoimplant 2020 1st place: 3D U-Net Architecture with full depth

SAU-Net Architecture (Sun et al. 2020)

The model achieves SOTA results on the two large public cardiac MRI image segmentation datasets of SUN09 and AC17.

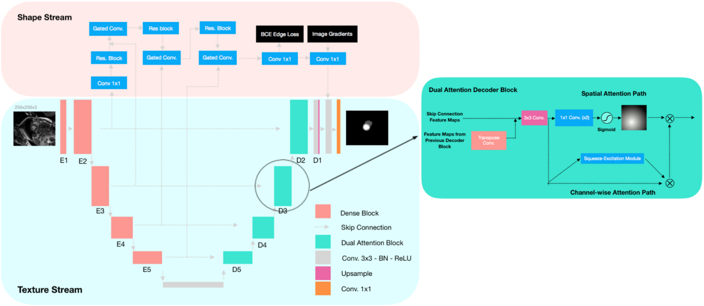

Figure: SAU-Net Architecture

Metrics & Results

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- Dice Similarity Score (DSC)
- Hausdorff Distance (HD)
- Boundary DSC (bDSC)

Table: Final results.

Experiment	DSC	HD	bDSC
One-Stage	$.71 \pm .05$	11.07 ± 2.85	$.034 \pm .01$
One-Stage DL	$.72 \pm .05$	10.68 ± 2.76	$.034 \pm .010$
One-Stage reg	$.73 \pm .05$	10.49 ± 2.85	$.034 \pm .010$
Two-Stage	$.80 \pm .03$	20.50 ± 8.79	$\underline{.055 \pm .014}$
3D U-Net	$\underline{.84 \pm .02}$	26.13 ± 9.43	$.028 \pm .009$
SAU-Net	$.75 \pm .03$	$\underline{8.79 \pm 2.99}$	$.034 \pm .010$

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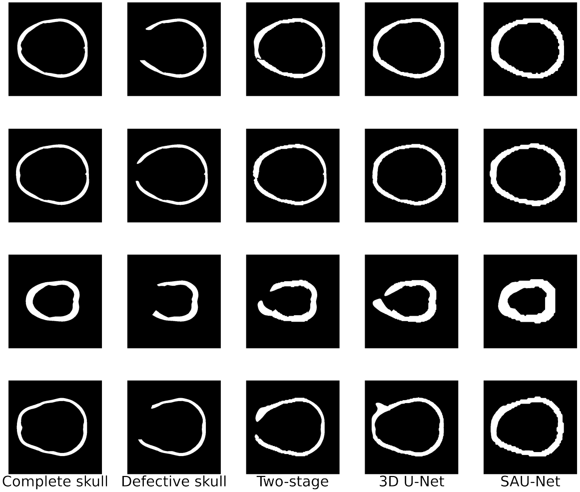
Visualisation

Examples of skull reconstruction for 3 best models



Conclusions

- Important medical problem
- Diversity of algorithms for automatic cranioplasty
- Simple solutions can achieve good results even with restricted time and computational resources

Team member's contributions

Mariya Donskova (20% of work)

- Biomedical & DL Literature Review (2 papers)
- Preparing Metrics Calculation
- Preparing Video & Presentation
- Preparing Github Repo

Aleksandr Nevarko (20% of work)

- DL Literature Review (2 papers)
- Developing SAUNet, 3D U-Net
- Preparing Video & Presentation
- Preparing GitHub Repo

Alexey Shevtsov (20% of work)

- DL Literature Review (2 papers)
- Developing All the Models
- Preparing Video & Presentation
- Preparing Github Repo

Konstantin Soshin (20% of work)

- Biomedical & DL Literature Review (2 papers)
- Developing Baseline Models
- Preparing Video & Presentation
- Preparing GitHub Repo

Anita Soloveva (20% of work)

- Biomedical & DL Literature Review (2 papers)
- Data Augmentation
- Preparing Video & Presentation
- Preparing GitHub Repo

References

Baldassano, S., Zhao, X., Brinkmann, B., Křemen, V., Bernabei, J., Cook, M., Denison, T., Worrell, G., and Litt, B. Cloud computing for seizure detection in implanted neural devices. *Journal of Neural Engineering*, 16, 12 2018. doi: 10.1088/1741-2552/aaf92e.

Egger, J., Gall, M., Tax, A., Üçal, M., Zefferer, U., Li, X., von Campe, G., Schäfer, U., Schmalstieg, D., and Chen, X. Interactive reconstructions of cranial 3d implants under mevislab as an alternative to commercial planning software. *PLoS ONE*, 12:20, 03 2017. doi: 10.1371/journal.pone.0172694.

Ellis, D. G. and Aizenberg, M. R. Deep learning using augmentation via registration: 1st place solution to the autoimplant 2020 challenge. In Li, J. and Egger, J. (eds.), *Towards the Automatization of Cranial Implant Design in Cranioplasty*, pp. 47–55, Cham, 2020. Springer International Publishing.

Kodym, O., Li, J., Pepe, A., Gsaxner, C., Chilamkurthy, S., Egger, J., and Španěl, M. Skullbreak / skullfix – dataset for automatic cranial implant design and a benchmark for volumetric shape learning tasks. *Data in Brief*, 35:106902, 02 2021. doi: 10.1016/j.dib.2021.106902.

Křemen, V., Brinkmann, B., Kim, I., Guragain, H., Nasseri, M., Magee, A., Attia, T., Nejedly, P., Sladky, V., Nelson, N., Chang, S.-Y., Herron, J., Adamski, T., Baldassano, S., Cimbalnik, J., Vasoli, V., Fehrmann, E., Chouinard, T., Patterson, E., and Worrell, G. Integrating brain implants with local and distributed computing devices: A next generation epilepsy management system. *IEEE Journal of Translational Engineering in Health and Medicine*, 6, 09 2018. doi: 10.1109/JTEHM.2018.2869398.

Li, J. and Egger, J. Towards the automatization of cranial implant design in cranioplasty, 03 2020.

Li, J., Pepe, A., Gsaxner, C., von Campe, G., and Egger, J. A baseline approach for autoimplant: the miccai 2020 cranial implant design challenge. *arXiv preprint arXiv:2006.12449*, 06 2020.

Lázaro-Muñoz, G., Yoshor, D., Beauchamp, M., Goodman, W., and McGuire, A. Continued access to investigational brain implants. *Nature Reviews Neuroscience*, 19, 04 2018. doi: 10.1038/s41583-018-0004-5.

Matzkin, F., Newcombe, V., Stevenson, S., Khetani, A., Newman, T., Digby, R., Stevens, A., Glocker, B., and Ferrante, E. Self-supervised skull reconstruction in brain ct images with decompressive craniectomy, 07 2020.

Morais, A., Egger, J., and Alves, V. *Automated Computer-aided Design of Cranial Implants Using a Deep Volumetric Convolutional Denoising Autoencoder*, pp. 151–160. 04 2019. ISBN 978-94-024-1613-8. doi: 10.1007/978-3-030-16187-3_15.

Sun, J., Darbehani, F., Zaidi, M., and Wang, B. Saunet: Shape attentive u-net for interpretable