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

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Abstract

Automatic design of cranial implant has long been an under-researched area. Thus, the goal of the project is to 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. For that purpose we make use of the AutoImplant 2021 Challenge dataset. As baseline solutions, we employ 1) the two-stage approach based on separate autoencoders for generating the implant first in low-, then high resolution; 2) one autoencoder that aims to reconstruct the incomplete skull in low-resolution space. As for the architectural competitor, we take Shape Attentive U-Net (SAUNet) that achieves SOTA results on the two large public cardiac MRI image segmentation datasets of SUN09 and AC17.

Github repo: Autoimplant-2020-2021
Video presentation: drive.google.com

1. Introduction

Automatic cranial implant generation can reduce overall patient risks and operating time by computing the implant shape for a specific patient based on CT scan of their head (Chen et al. 2017). The AutoImplant 2020 Cranial Implant Design Challenge and its substantial extension in 2021 aim to test various approaches for designing an implant based on brain CT images.

A baseline solution for the first challenge provided by the organizers (Li et al. 2020) was a cascade style set of models where the first one predicts the implant's shape at low-resolution, and the second one refines that shape at high-resolution. On the test set, this approach achieved an average dice similarity score (DSC) of 0.8555 and Hausdorff distance (HD) of 5.1825 mm. Inspired by these results, we employ a two-stage method based on separate autoencoders for designing the implant first in low-, then high resolution as our first baseline solution.

Another type of approaches to the considered task is to reconstruct the complete version of the skull. In (Morais et al. 2019) for that purpose an encoder-decoder network is proposed. Initially one gets a complete, but low-resolution skull model as an output, which is then correlated with shape priors, being processed by a 3D shape synthesis method in order to generate an output in high resolution. In our study we use a similar approach as a second baseline solution.

The main goal of the project is to raise the quality of automatically generated cranial implants by increasing the dataset size with two different augmentation techniques and a more complex architecture. For the dataset, we apply 1) the extraction of spherical and cubic defects of different size and localization from the complete skulls to match with standard surgeries; 2) automatic co-registration between the given skull masks. We take Shape Attentive U-Net (SAUNet) that focuses on model interpretability and robustness.

The main contributions of this paper are:

- Section 2 is devoted to the discussion of the recent papers on automatic cranial implant generation.
- In Section 3 we provide the description of:
  - Baseline Solutions
  - Dataset and Data Augmentation
  - Architectural Competitor
- In Section 4 we represent the obtained results of:
  - Baseline solution with and w/o data augmentation
  - Architectural Competitor with and w/o data augmentation

2. Related work

2.1. Baseline: One-Stage (Morais et al. 2019)

As baseline solution we took this paper from 2019. This approach doesn't include any dataset expansion techniques. This is a network, trained in an unsupervised fashion to predict the input uncorrupted skull. So, after training, network learns latent space of skulls. Then on inference stage, having the damaged skull as an input it outputs skull without

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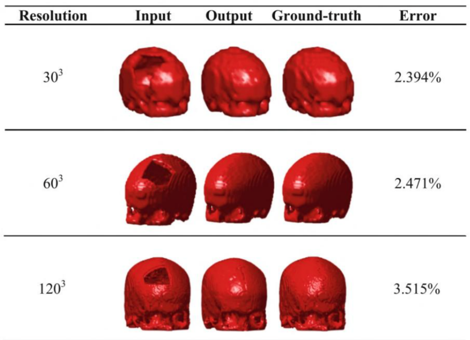


Figure 1. Examples of autoencoder output for different resolutions.

hole. In original paper the experiment were conducted in three different voxel resolutions. Since the network has a lot of 3d convolutional layers it was very memory-consuming and in fact it was a big pain to train it. For example, for resolution 60 x 60 x 60 it requires 21 gb of memory. So it is almost impossible to train on the whole skulls on resolution higher than 64. However, this architecture can give satisfactory results already in first epochs

2.2. Baseline: Two-Stage (Li et al. 2020)

A baseline approach provided by the organizers of Autoimplant 2020 is a cascade style set of models, which generates high-quality implants in two stages. First, one autoencoder learns a coarse implant representation from down-sampled, defective skulls in order to generate the bounded area of the defected region in the original high-resolution skull. Second, another autoencoder generates a fine implant from the bounding box. Despite the fact that such solution has a great advantage of limiting memory use, authors mention several limitations of it. The main one is that the proposed model cannot accurately predict implants for the defects that are in different locations and differently shaped than the defects in the training set. As we stated above it takes a lot of memory to process skull in high resolution. So our next approach includes two networks. First, is the same autoencoder which works in low resolution. Its prediction is used for localization of defected region. Just by subtracting input damaged skull from predicted one we obtain region with implant. Then we crop the area with defected region, but in higher resolution and use second network to make implant for that area.

2.3. UNet Architecture

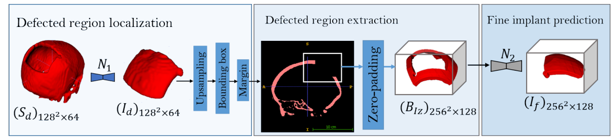


Figure 2. Two-stage model scheme

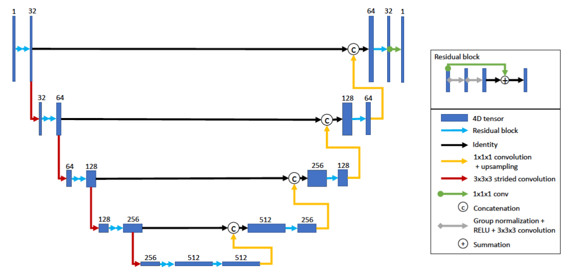


Figure 3. Autoimplant 2020 1^{st} place: 3D U-Net Architecture with full depth

Next we looked at 2020 challenge winners used a simple 3d UNet architecture with skip connections in their work, so we decided to implement it. We had two variations: a thin networks with less layers and a more shallow bottleneck and a full scale UNet. It consists of 3d convolutions and pre activation residual blocks.

2.4. SAUNet Architecture

After that, we decided to try some new models, not seen previously. We found the shape-attentive-unet, that showed State of the Art result in segmentation for 2D pictures in 2020. It's uniqueness is that it has a shape stream, that learned to process geometrical shapes from a 1-channeled image. Also the decoder consists of dual attention blocks. Those factors made us think that this network may work on our data. We reimplemented this network for volumetric 3d data preserving the architecture. Unfortunately, the model requires a lot of memory, so we were limited in our experiments.

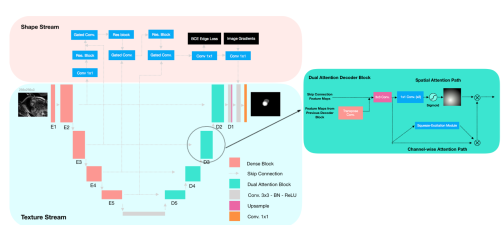


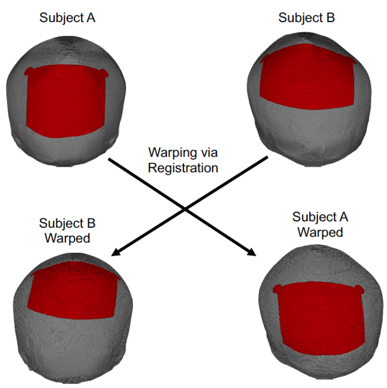
Figure 4. SAU-Net Architecture

3. Algorithms and Models

3.1. Dataset Description & Data Augmentation

We use the AutoImplant 2021 Challenge dataset, which contains 114 3D binary skull masks of size 512^3. Each has the corresponding pair with different types of artificially generated defect in the particular region (bilateral, frontoorbital, parietotemporal) or random. All the skulls were roughly aligned into standardized position in order to reduce positional variability.

For the purpose of expanding the size of the training dataset in order to avoid overfitting we resort to two techniques of data augmentation. The first one is Virtual Craniectomy procedure proposed in (Matzkin et al. 2020). The process implies extracting the intersection of each complete skull with a spheric- and cubic-shaped binary masks of a variable size that can be located in its upper part (in the lower part containing the bones between the jaw and the spine a craniectomy cannot occur). The radius of the sphere and the side of the cube are established so that it would match with standard surgeries.



The second data augmentation technique we use is an automatic co-registration between the given skull masks utilizing the Advanced Normalization Tools (ANTs) package. In (Zhao et al. 2019) such method was reported to be highly effective at augmenting small training datasets of medical images. Moreover, 1st Place Solution to the AutoImplant 2020 Challenge (Ellis & Aizenberg 2020) also made use of this augmentation method. In our study, N random complete skull images were registered with and warped into the space of N other images. Combined with the original training images, this resulted in an augmented dataset of XX images.

We do not use any other data pre-processing, such as, for instance, min-max or z-score normalization (PATRO & Sahu 2015), which is usually applied to MRI images in order to remove the scanner variation and focus more on variations in the morphology of the skull (Li et al. 2019), since CT scans have a standard intensity scale and this procedure will not produce the desired effect.

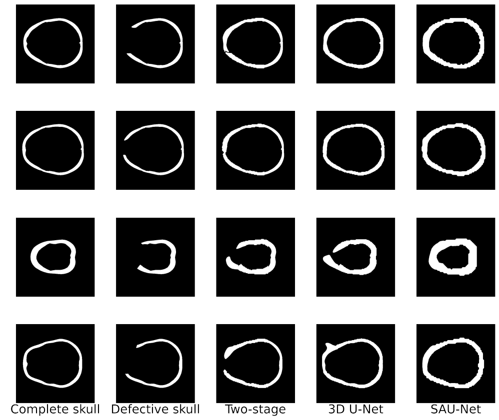


Table 1. Final results.

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	$.75 \pm .03$	$\underline{8.79 \pm 2.99}$	$.034 \pm .010$

4. Results

Main results of our work can be seen from table.

In the picture we can see the results of all architectures, bad and good cases.

5. Conclusions

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

A. Team member's contributions

Mariya Donskova (20% of work)

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

Aleksandr Nevarko (20% of work)

- Reviewing literature on the topic (2 papers)
- Developing SAUNet
- Preparing the GitHub Repo
- Preparing the presentation
- Preparing Report

Alexey Shevtsov (20% of work)

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

Konstantin Soshin (20% of work)

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

Anita Soloveva (20% of work)

- Reviewing literature on the topic (2 papers)
- Data Augmentation
- Preparing the GitHub Repo
- Preparing the presentation
- Preparing Report

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