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

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Mariya Donskova<sup>1</sup> Aleksandr Nevarko<sup>1</sup> Alexey Shevtsov<sup>1</sup> Konstantin Soshin<sup>1</sup> Anita Soloveva<sup>1</sup>

## 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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<sup>1</sup>Skolkovo Institute of Science and Technology, Moscow, Russia. Correspondence to: Konstantin Soshin <Konstantin.Soshin@skoltech.ru>.

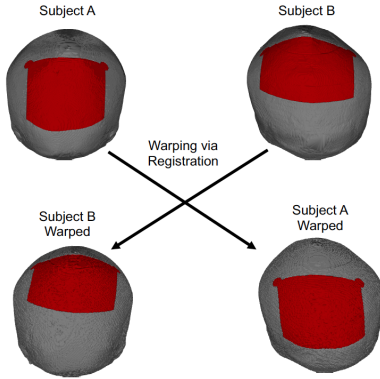


### 3. Algorithms and Models

#### 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, fronto-orbital, 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

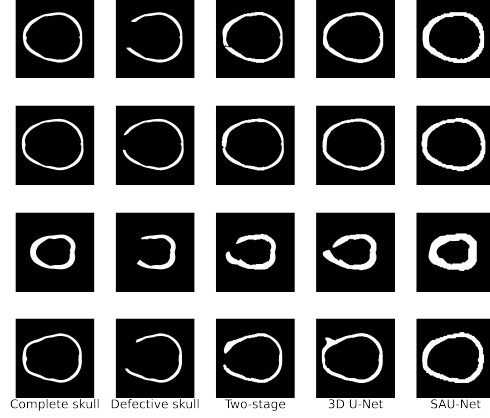


Table 1. Final results.

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

not produce the desired effect.

### 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)

- Reviewing literature on the topic (2 papers)
- Preparing the metrics
- Preparing the presentation
- Preparing Sections XX of the report

### Aleksandr Nevarko (20% of work)

- Reviewing literature on the topic (2 papers)
- Developing SAUNet
- Preparing the GitHub Repo
- Preparing the presentation
- Preparing Sections XX of the report

### Alexey Shevtsov (20% of work)

- Reviewing literature on the topic (2 papers)
- Developing the baseline solution
- Preparing the GitHub Repo
- Preparing the presentation
- Preparing Sections XX of the report

### Konstantin Soshin (20% of work)

- Reviewing literature on the topic (2 papers)
- Developing the baseline solution
- Preparing the GitHub Repo
- Preparing the presentation
- Preparing Sections XX of the report

### Anita Soloveva (20% of work)

- Reviewing literature on the topic (2 papers)
- Data Augmentation
- Preparing the GitHub Repo
- Preparing the presentation
- Preparing Sections XX of the report

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