A Baseline Approach for AutoImplant: the MICCAI 2020 Cranial Implant Design Challenge

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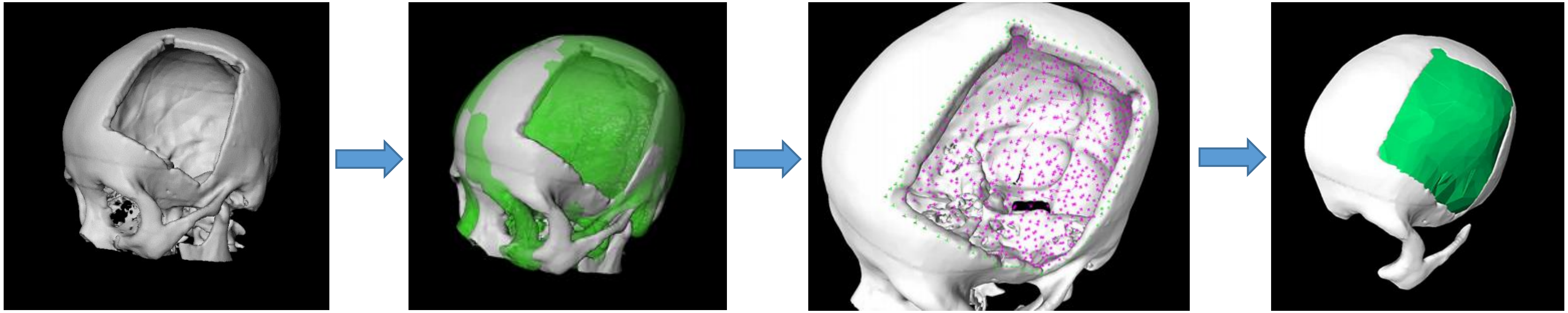
Motivation

Interactive Cranial Implant Design:



a). Post-craniotomy skull model

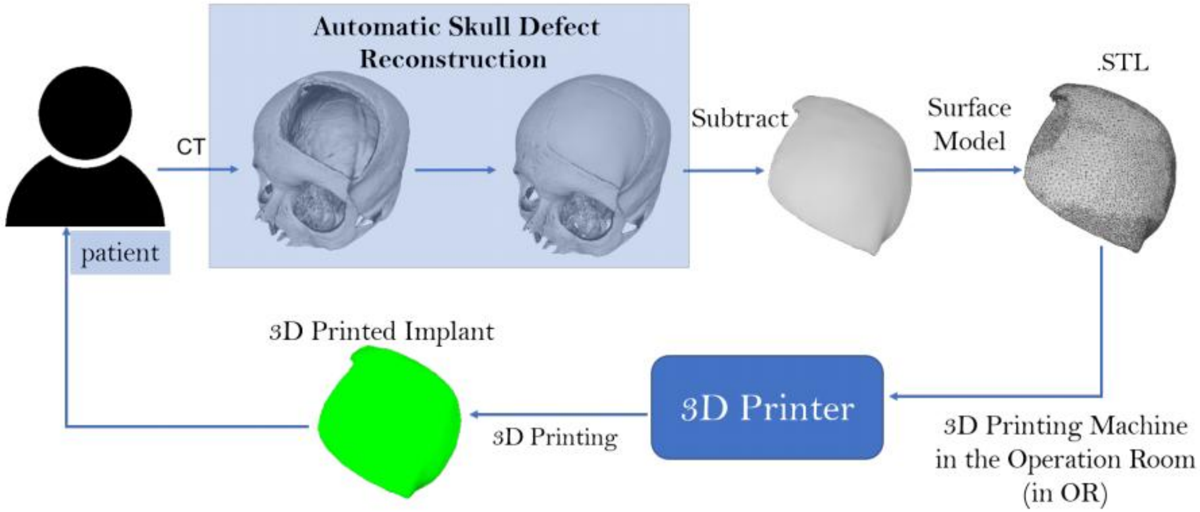
b). Mirroring along skull symmetry plane

c). Postprocessing

d). Final cranial implant (green)

- high cost (commercial)
- time-consuming
- experience-dependent

Automatic Cranial Implant Design:



- low cost
- fast
- in operation room (in-OR) design & manufacturing
- user-independent

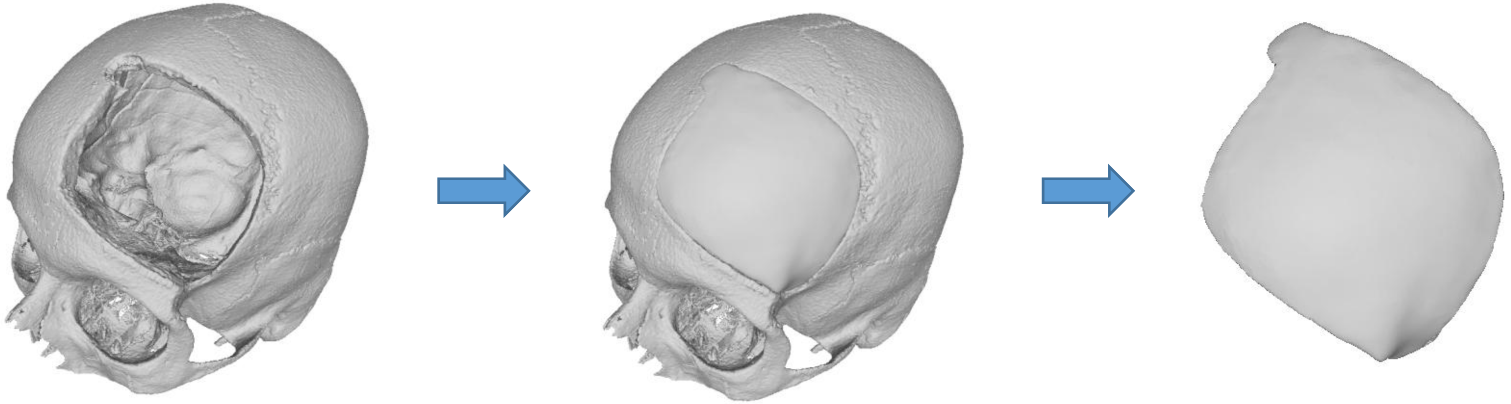
Technical Formulation

(Volumetric) shape completion

Subtraction

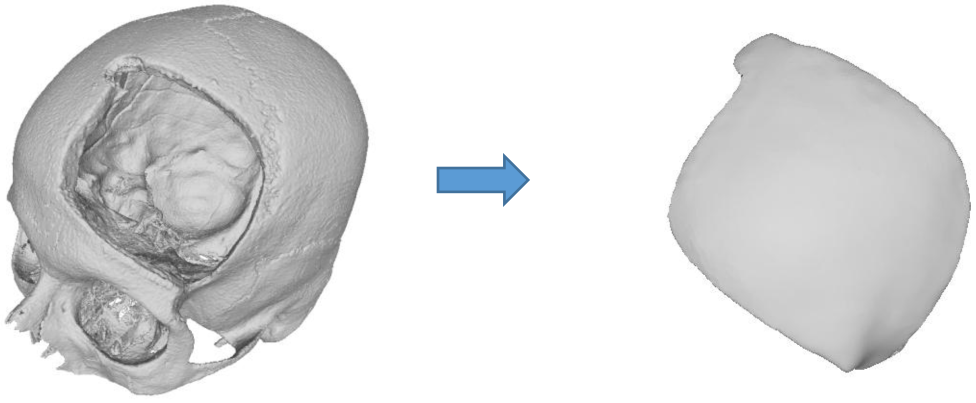
1.

Defective skull
↓
Complete skull
↓
Cranial implant



2.

Defective skull
↓
Cranial implant



Defective skull

Cranial implant

Related Work

Automatic skull reconstruction:

- Statistical shape model (SSM)[1]
- Deep Learning[2]

Similarity:

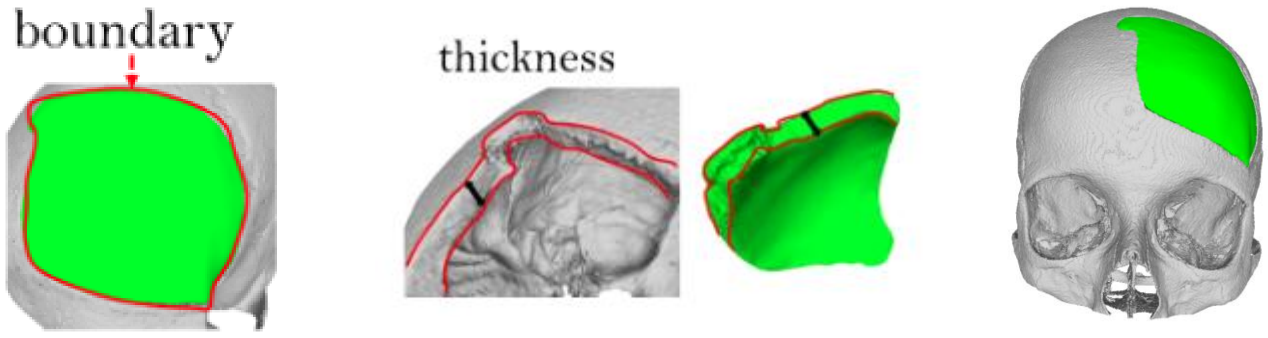
- Fully data-driven (training set)
- Using artificial skull defects

Difference:

- SSM: skull mesh
- Deep learning: skull voxel grid

Challenges:

- High dimensionality: $512 \times 512 \times Z$
- 3D Shape learning: geometric priors?
    - Boundary consistency (A)
    - Bone thickness consistency (B)
    - Shape consistency (C)



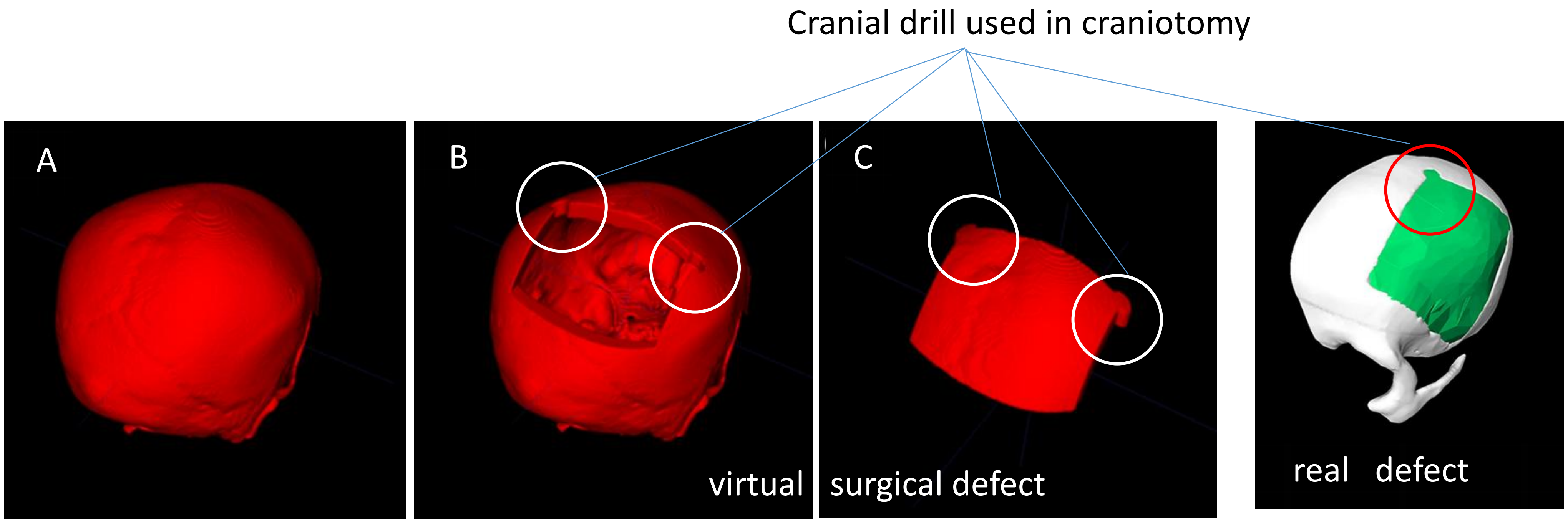
(A) (B) (C)

[1]Fuessinger, M. A. et al. (2017). "Planning of skull reconstruction based on a statistical shape model combined with geometric morphometrics."
[2]Morais, A. et al. (2019). "Automated Computer-aided Design of Cranial Implants Using a Deep Volumetric Convolutional Denoising Autoencoder."

Dataset

Dataset Creation:

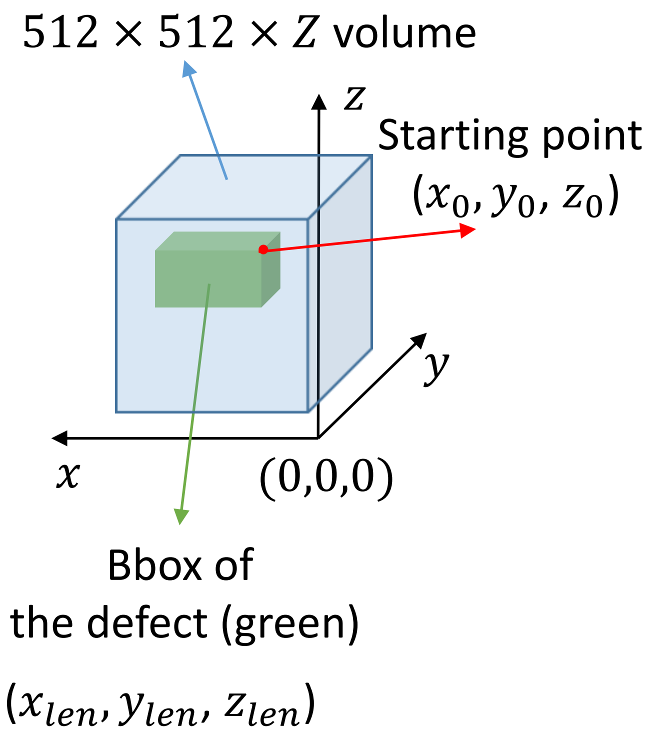
- 200 unique skulls[1] for training (100) & testing (100)
- Head CT Segmentation: thresholding (HU 150~max)
- Automatic Defect injection: segmentation (A), defective (B), implant (C)

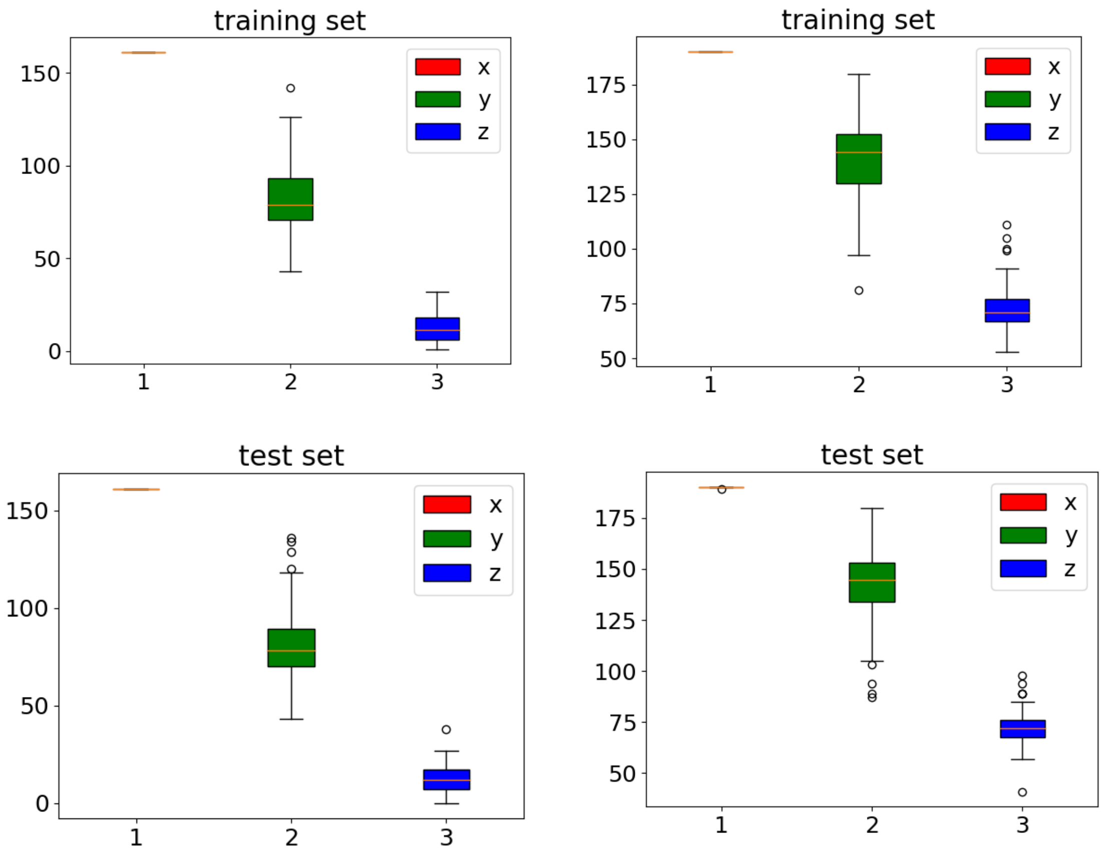


[1] Head CT CQ500 (http://headctstudy.qure.ai/dataset)

Defect Variations:

- Each skull has unique shape.
- The defects vary w.r.t. shape, size and position (quantitatively).





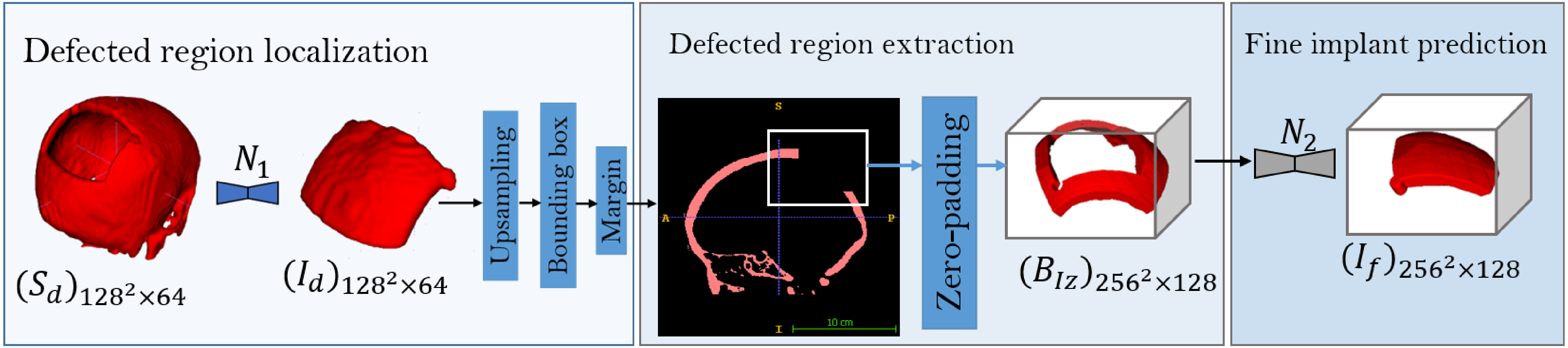
Position variation

(x_0, y_0, z_0)

Size variation

$(x_{len}, y_{len}, z_{len})$

A Coarse-to-fine framework



- A coarse implant can be learnt from downsampled data.
- The coarse implant provides the ***spatial information*** of the defected region.
- Fine implant can be learnt from the defected region (not the whole data) with some surrounding information.

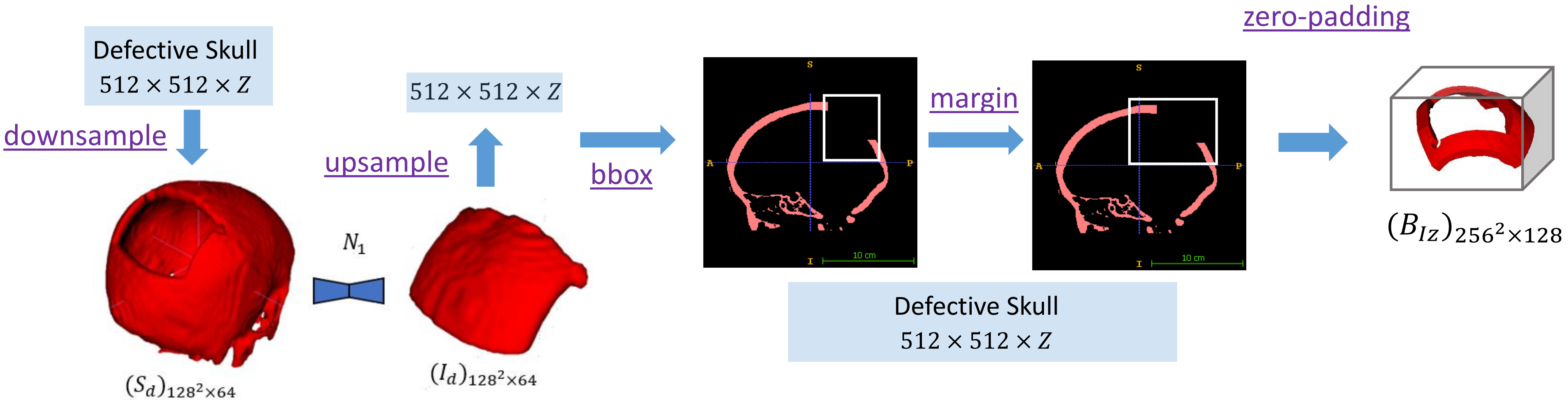
Configurations & Implementation

- How to extract the defected region?
    1. Coarse implant prediction
    2. Upsampling
    3. Bounding box
    4. Margin
    5. Zero-padding

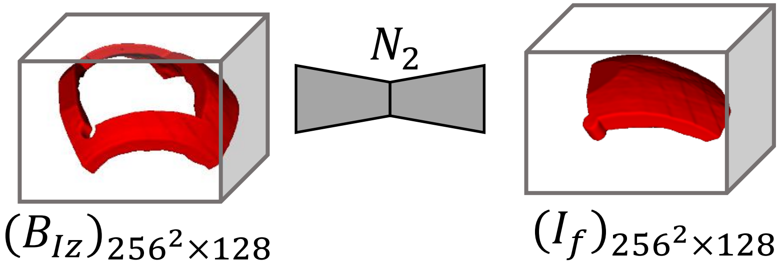
- How is N1 and N2 chosen?
    1. Architecture: A fully convolutional autoencoder
    2. Parameters

- How to transform the fine implant back to the original dimension?

- How to extract the defected region?
    1. **Coarse implant prediction:** predict coarse implant from downsampled skull $128 \times 128 \times 64$
    2. **Upsampling:** interpolating the coarse implant to its original dimension $512 \times 512 \times Z$
    3. **Bounding box(bbox):** a bounding box tightly encloses the defected region $X \times Y \times 128$
    4. **Margin:** include some surrounding skull $(X+2m) \times (Y+2m) \times 128, m = 10$
    5. **Zero-padding:** to make the extracted defected region have the same dimension $256 \times 256 \times 128$



- Predict fine implant from the extracted region



- How is N_1 and N_2 chosen?
  1. architecture: A fully convolutional autoencoder style network
  2. parameters: N_2 (~0.6***m***) has to be much lighter than N_1 (~82***m***) to contain the GPU memory

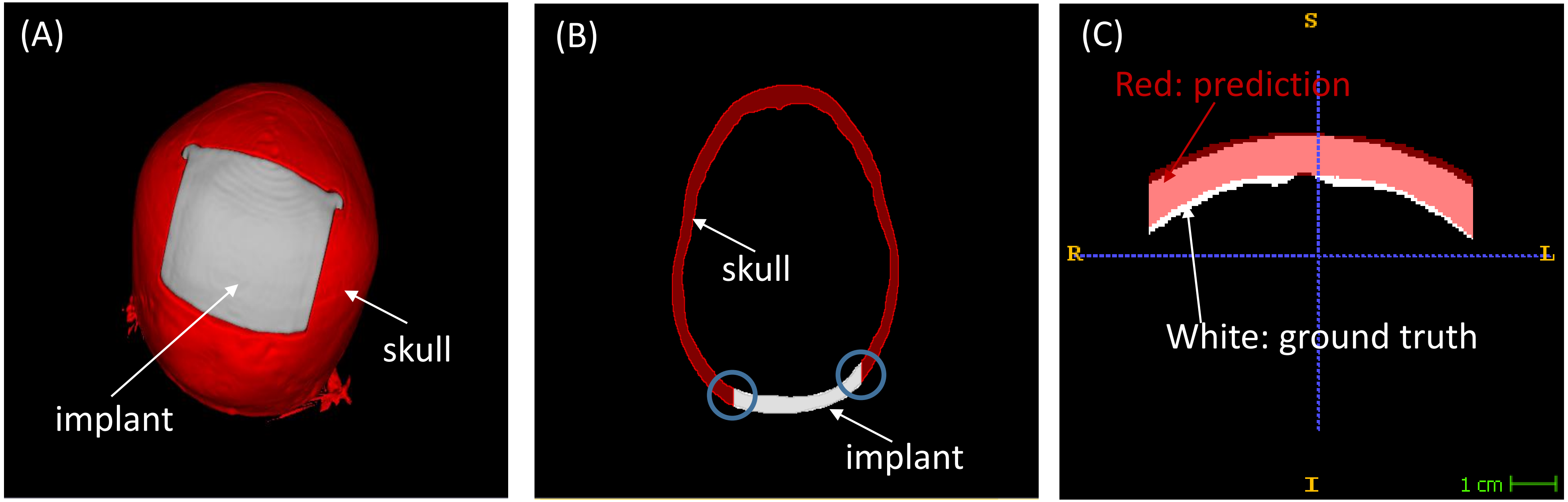
- How to transform the fine implant back to the original dimension?

$$256^2 \times 128 \rightarrow 512^2 \times Z$$

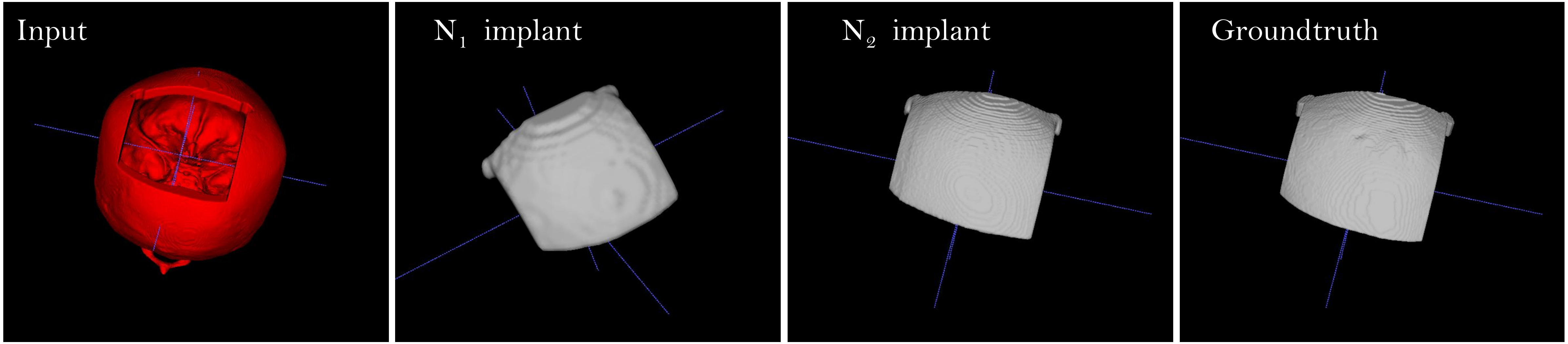
An inverse process of zero-padding and margin applying

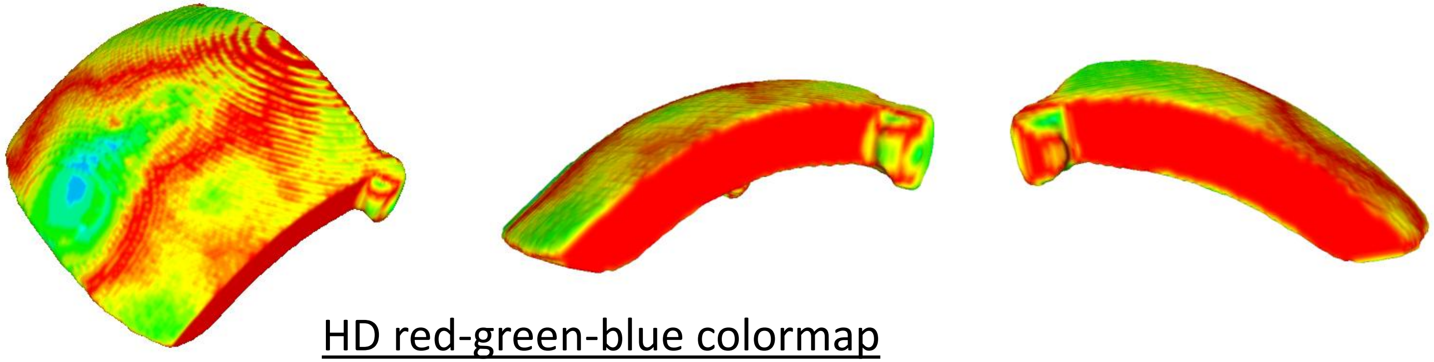
Results

- **Quantitative:** mean DSC 0.8555 mean HD 5.1825*mm*, mean RE 0.15%
- **Qualitative:** boundary (A), bone thickness (B) and shape (C)



Curvature



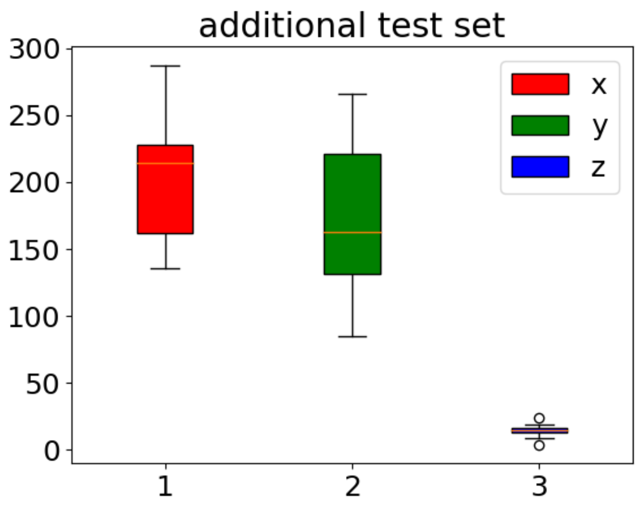


HD red-green-blue colormap

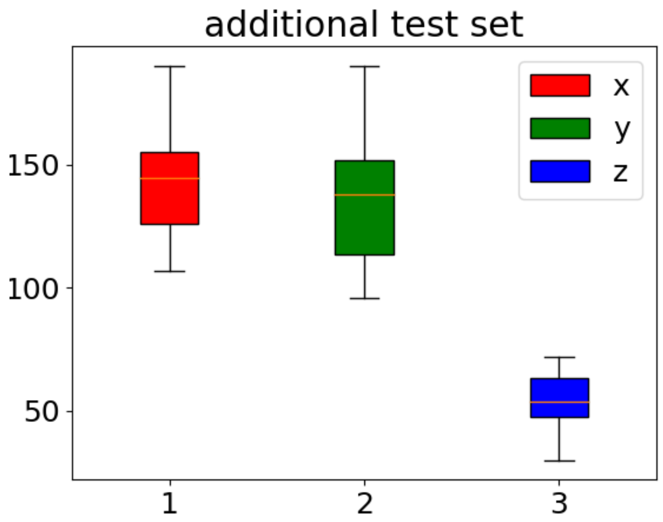
- N_1 implant: lacking surface geometric details
- N_2 implant: surface geometric details reconstructed
- the implant matches well with the ground truth especially on the boundary (red)

Limitations

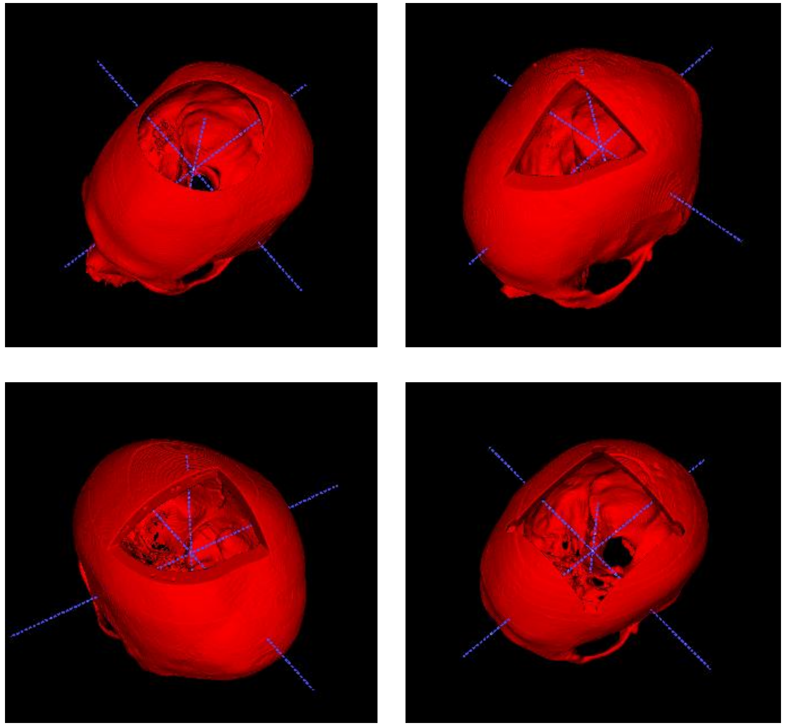
- trained and evaluated only on synthetic defect.
- N_2 tends to fail on highly varied defects.



Position variations



Size variations



Shape variations

Conclusion

- Shape learning can be fully data-driven, without relying on geometric shape priors (N_1).
- The learning can be carried out on the defected region with limited surrounding information instead of on the entire skull shape, which saves computation (N_2).
- A **coarse-to-fine framework** that facilitates the processing of high dimensional data with limited GPU memory.
- A baseline for the MICCAI 2020 AutoImplant Challenge.

Future Work

- Generation of more realistic craniotomy defects
- Evaluation on real craniotomy data

Dataset: AutoImplant Challenge

https://autoimplant.grand-challenge.org/

Source code:
https://github.com/Jianningli/autoimplant

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