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A Deep Learning based Fast Signed Distance Map Generation

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Signed Distance Map

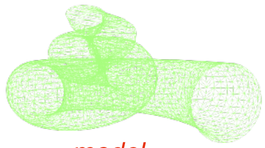
1. SDM and Motivation

Definition *: SDM is a scalar image f(x) giving the signed distance of each voxel x to a given (closed) surface mesh:* $|\nabla f| = 1$

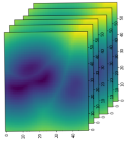
Why is it useful ?

- Encapsulate shape with probabilitic models

- Defined attention weight maps for Neural Networks design etc.



- model



- SDM

2. Prior works

- Naïve complexity is $O(Nn)$ *complexity. (N is number of voxels, n is number of triangles.)*

- Fast computation of 2D and 3D SDM possible with graphics processing units (GPU).

- CNN-based signed distance computation for a single point in space

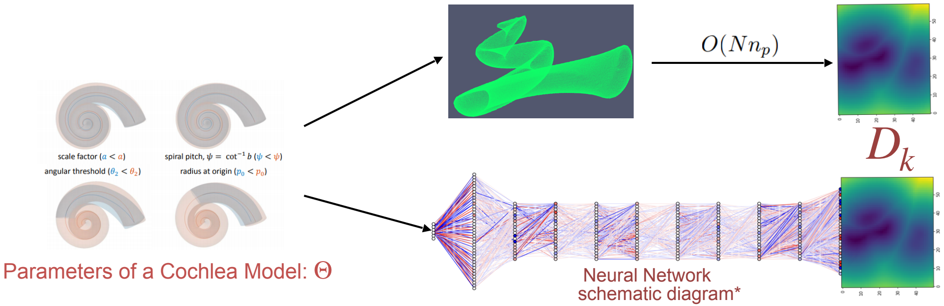
Problem : Fast Generation of SD Images for Parametric Meshes

Roosing, A., et al. Fast distance fields for fluid dynamics mesh generation on graphics hardware.
Jeong Joon Park, et al. Deepsdf: Learning continuous signed distance functions for shape representation
Zhiqin Chen and Hao Zhang. Learning implicit fields for generative shape modeling

Our solution

1. Signed Distance Mapping through CNN

- *Network linking Directly shape parameters Θ_i to SDM scalar set D_k:*

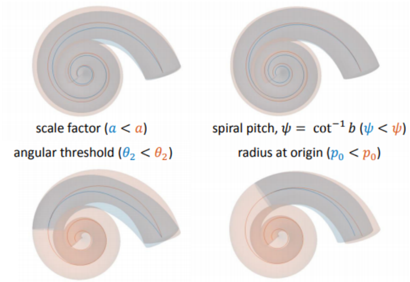


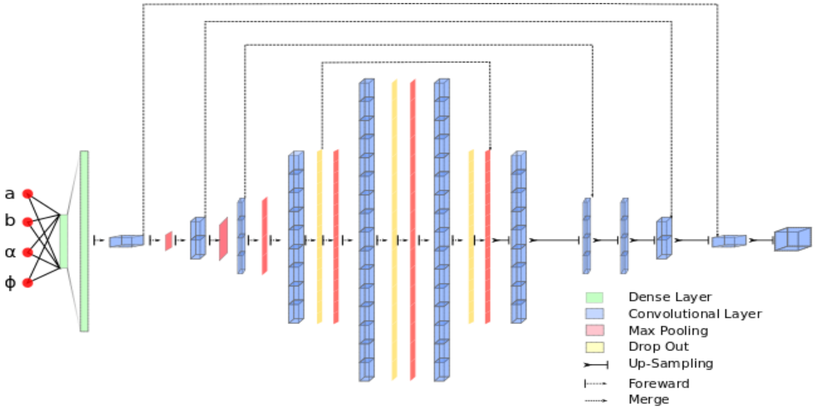
- *Naïve algorithm with high time complexity.*
- *Time CNN method with time complexity O(Nc), where c is the number of CNN parameters .*

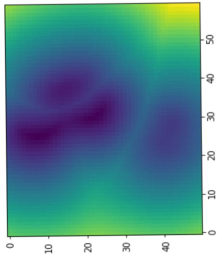
Proposed network SDMNN

1. Mapping through CNN

- An encoder-decoder network with merged layers inspired by the well known U-net (Ronneberger et al., 2015).







- The SDMNN was trained on one NVIDIA 1080Ti GPU for 168 hours.
- Training set include static 625 vector - tensor pairs and online random generated SDMs
- Simple Mean Square Error (MSE) loss is sufficient.

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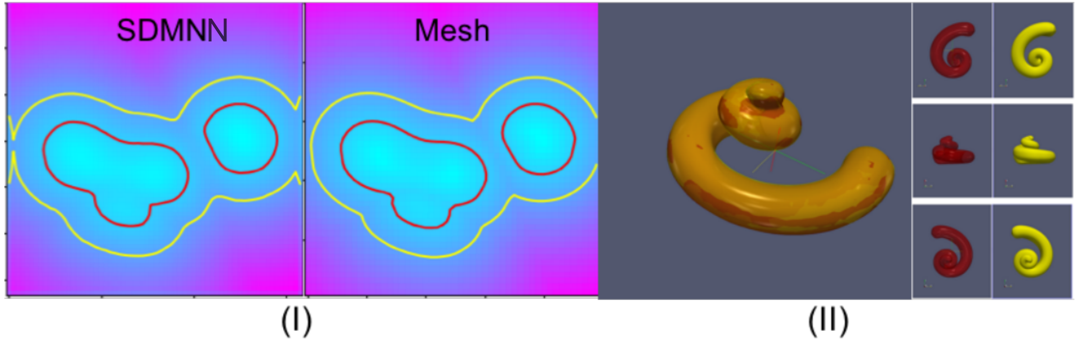
Qualitatively Result

1. Accuracy Comparison



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Quantitatively Result

1. Computational Efficiency

TABLE 1: DIFFERENT METHODS COMPUTATIONAL TIME FOR SDM GENERATION

GENERATION TIME	SDMNN	Mesh Based SDM	DeepSDF *
SINGLE SDM	0.2 Sec	10.7 Sec	28.1 Sec
SHAPE FIT	1:05:02.1 H	12:15:45.4 H	FAILED

[*] Jeong Joon Park et al. DeepSDF: Learning Continuous Signed Distance Functions for Shape Representation, 2019, CVPR

2. Parameters Inference Accuracy

Applied both mesh based SDM and proposed SDMNN in a Bayesian frame work to inference 9 cochlea shape model and compare the difference of shape parameters.

Table 2: Shape parameters estimation error for SDMNN compared to mesh based SDM

Parameters Name Parameters Range	a (2.0, 5.0)	α (0.0, 1.2)	b (0.05, 0.25)	φ $(-\pi/4, \pi/4)$
Mean shape parameters errors P_{err} on 9 cases.	2.06e-08	2.53e-08	5.4e-08	1.00e-09

Limitation and Summary

1. Limit

- The training process of full 3D CNN need a large GPU memory.
- Only suitable when the number of shape parameters is small

2. Summary

- A deep learning method for fast SDM generation.
- Mapping between shape parameters space to distance vector space.
- No GPU needed during SDM generation.

Thank you!