A Deep Learning based Fast Signed Distance Map Generation

Anonymous Author(s)
Affiliation
Address
`email`

Abstract

Signed distance map (SDM) is a common method to represent the shape of structures in medical image analysis. The computational complexity of SDM is a main problem in many cases that is limiting the application of SDM. In this paper we propose a learning based SDM generation neural network which is demonstrated on a tridimensional cochlea shape model parameterized by 4 shape parameters. The proposed SDM Neural Network generates the cochlea signed distance map depending on the four input parameters and we show that the deep learning approach leads to a significant improvement in the time of computation compared to more classical SDM generation methods. Therefore, the proposed approach achieves a good trade-off between fidelity and efficiency.

Keywords: Signed Distance Map, Deep Learning

1 Introduction

A Signed Distance Map (SDM)(Tsai and Osher (2003)) $f(\mathbf{x})$ is a scalar field giving the signed distance of each point to a given (closed) surface, which mathematically translated into the relation $\|\nabla f\| = 1$. In practise, SDMs are 2D or 3D images storing the distance of each voxel center and are widely used to tackle various problems in computer vision or computer graphics fields. In machine learning, SDMs are useful to encode the probability to belong to a shape through log-odds mapsPohl et al. (2006). For instance, given a surface $\mathcal{S}(\theta_S)$ and a scalar l_{ref}, the probability for a voxel n having position $\mathbf{x}_n$ to belong to the surface can be provided through the SDM $\mathrm{SDM}(\mathcal{S}(\theta_S), \mathbf{x}_n)$ at that voxel as $p(Z_n = 1) = \sigma\left(\frac{\mathrm{SDM}(\mathcal{S}(\theta_S), \mathbf{x}_n)}{l_{\text{ref}}}\right)$ where $\sigma(x)$ is the sigmoid function.

While there exist fast (linear complexity) sweeping methodsMaurer et al. (2003) for computing SDM from binary shapes, the naive computation of an SDM from triangular meshes has complexity $O(Nn_T)$ where N is the number of image voxels and n_T is the number of triangles describing the shape. An example of a generic computation of SDM from meshes is available in VTK Quammen et al. (2011); Baerentzen and Aanaes (2005) through the *vtkImplicitPolyDataDistance* class. Since many algorithms are relying on the SDM generation, it is critical to optimize its computation time in various ways Jia et al. (2018). In medical image analysis, the naive approach leads to poor performances due to the fact that volumetric images and complex shapes are considered. To improve the performance of the SDM calculation, Hoff *et al.* Hoff et al. (2002) proposed 2D and 3D SDM computation methods that take advantage of graphics processing units (GPU) in order to accelerate the computation. Recently, Roosing et al. (2019) proposed a fast distance field generation method for computing fluid dynamics meshes, also based on GPU parallel computing acceleration. Yet, there does not exist any generic library for fast computation of SDM on GPU, and the availability of specific GPU at test time is a significant limitation for machine learning applications.

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Algorithmic optimizations were proposed by various authors Jones et al. (2006) for instance by adopting hierarchical data structures to reach an $O(N \log n_T)$ complexity. For instance, Complete Distance Field Representation (CDFR) Jian Huang et al. (2001) were introduced with triangles structured into 3D grids cells. Fast approximations of SDM was proposed as *Piece-wise Linear Approximation of SDM (PLASDM)* in Wu and Kobbelt (2003) based on structured piece-wise linear distance approximation.

Despite those prior work, there does not exist any generic and efficient way to compute SDM from a triangular mesh on a grid on CPU ressources. In this paper, we propose an alternative method for fast computation of SDM based on Convolutional Neural Network (CNN) Krizhevsky et al. (2012) which does not rely on the rasterization of mesh triangles and does not require any hardware acceleration at test time. Results showed that our approach reduces the SDM computational time complexity significantly without any significant impact on the accuracy of shape recovery.

2 Methods and Evaluation

The cochlea is an organ that transforms sound signals into electrical nerve stimuli to the cortex. Cochlea lesions can lead to hearing loss that can be improved by inserting Cochlear Implant(CI) for patients the middle and late stages of the disease. Cochlea shape analysis is a pivotal step for CI one state-of-art method for Cochlea Shape analysis is the work of (Demarcy (2017)) which makes a computationally intensive use of SDM computations inside Expectation-Maximization loops.

2.1 Cochlea Shape Model and Dataset

We rely on a parametric cochlea shape model that represents the shape variability of the human cochlea. It is represented as a generalized cylinder around a centerline having four shape parameters a, α, b, ϕ, two of them for the longitudinal (resp. radial) extent of the centerline. To compute the SDM of the shape model, the parametric surface was discretized as triangular meshes whose edge lengths are approximately 0.30±0.15 mm (Demarcy (2017)). The SDM were then generated by using VTK library and the *vtkImplicitPolyDataDistance* class which implements a naive SDM algorithm based on point-to-triangle distance computations.

For training the neural network, we generated a static dataset consisting of 625 $(5 \times 5 \times 5 \times 5)$ cochlea SDM datasets of size $50 \times 50 \times 60$ by uniformly sampling the 4 deformation parameters within user specified ranges. In addition, we performed random data augmentation, by generating online SDMs during the training stage through a random sampling of the 4 shape parameters.

2.2 Signed Distance Map Neural Network

Our SDM Neural Network (SDMNN) is an encoder-decoder network with merged layers, its structure being inspired by the well known U-net (Ronneberger et al. (2015)). The SDMNN has the four shape parameters as input and generates as output a $50 \times 50 \times 60$ signed distance map (see Fig. 1).

3 Experiments and Evaluation

The SDMNN was trained on one NVIDIA 1080Ti GPU with both static 625 datasets and online random SDMs with a Mean Square Error (MSE) loss for 168 hours. After training, we generated 300 test SDMs with the naive mesh-based VTK code that are associated with random shape parameters. Those were compared to the SDMs generated by the SDMNN for the same shape parameters and the MSE on the whole images were MSE = 0.002 which is very small given that the range of a SDM is $-0.01 + 0.003$.

Qualitative results are shown in Fig. 2 (I) where the comparison of the SDMNN and naive mesh-based generated maps is performed by extracting the isocontours associated with the zero (red) and 1mm (yellow) level sets. We see that the isocontours from the SDMNN match closely the ones generated from the mesh. Some small and smooth distorsions appear for the yellow contours. Since in surface reconstruction problems, the main focus of SDM is on the zero level set, the errors of the yellow isocontours are likely not to entail any major reconstruction errors. To verify the accuracy of the zero level isocontour, we have extracted the zero isosurface by the marching cubes algorithm associated

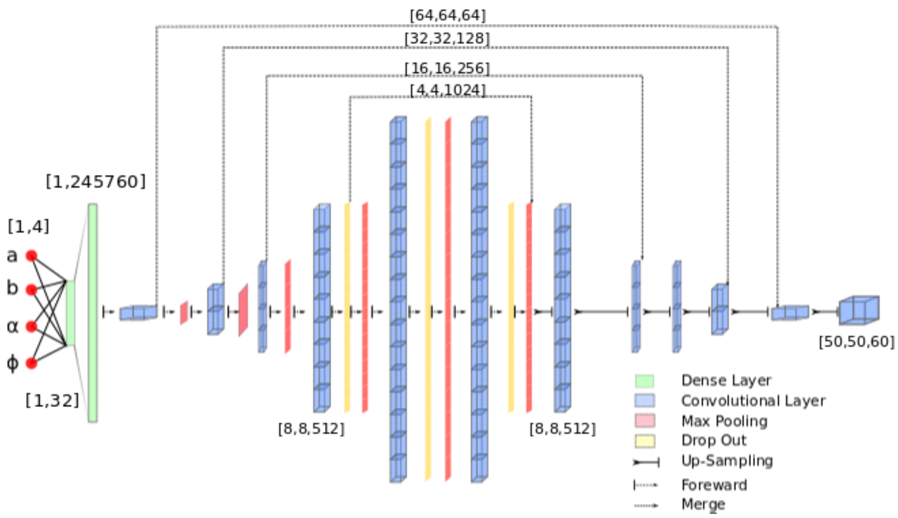

Figure 1: Proposed Signed Distance Map Neural Network (SDMNN)

with the standard shape values and compared that reconstructed surface with the original triangulated mesh model (the one used to generate the mesh SDM). In Fig. 2 (II) the 2 surfaces are overlaid showing that the SDMNN isosurface is as smooth as the original mesh and that the 2 surfaces are very close indeed.

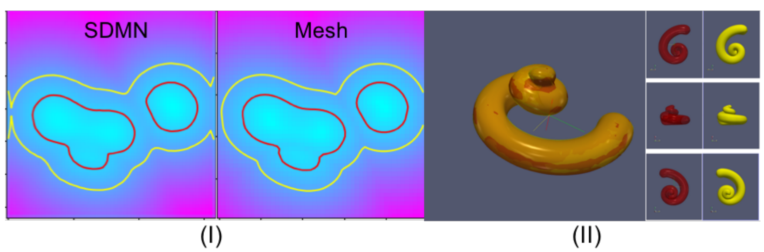

Figure 2: Isosurface difference between SDMNN and mesh based SDM generated distance map

The proposed approach is evaluated quantitatively in three ways. First, we compare the computation times between mesh based SDM generation and the SDMNN-based generation. All evaluations were performed on a Dell Mobile Workstation with Intel(R) Core(TM) i7-7820HQ @ 2.90GHz CPU. We show in Table 1 that the SDM neural network is about 66 times more efficient to generate a SDM than the classical method. Second, the performance was also compared on the fitting a cochlea shape model on a clinical CT image as in Demarcy (2017) which requires several hundreds of evaluations of sign distance maps. In such case, the speedup was shown to be about 11 times faster than the mesh based alternative.

Table 1: Computational time for SDMNN and mesh based SDM generation (Both on CPU)

Items	SDMNN	Mesh based SDM
Single SDM Generation Time	0:00:00.2	0:00:10.7
Cochea Shape Fit Computation Time	1:05:02.1	12:15:45.4

Thirdly, we evaluated the difference in terms of shape parameters by first using mesh based SDM to fit 9 clinical CT Cochlea volumes. This allowed to estimate the 4 shape parameters a, α, b, ϕ on each of the 9 cochleas that were stored in vector P_{mesh}. The same fitting process was applied by using the SDMNN to generate the SDM instead of the mesh-based method and obtained new shape parameters stored in P_{SDMNN}. The errors in shape parameters $P_{err} = \|P_{mesh} - P_{SDMNN}\|$ are reported in Table 2 showing negligible discrepancies given that the parameters magnitude is around 1 ($e \pm 1$).

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

Parameters Name Parameters Range	a (2.0, 5.0)	α (0.05, 0.25)	b (0.0, 1.2)	φ $(-\pi/4, \pi/4)$
Mean	2.06e-08	2.53e-08	5.4e-08	1.00e-09

4 Conclusions

In this paper, we proposed deep learning-based fast signed distance map generation method. We show quantitatively and qualitatively that our model can generate SDM in real-time, at the same time preserve the fidelity in an acceptable magnitude. This CNN based SDM generation model can be promoted to any parametric shape model for SDM generation. Besides, our model does not need extra GPGPU resources after training, which is conducive to the clinical environment costs control.

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