

Direct Volume Rendering with Nonparametric Models of Uncertainty

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Outline

- "Uncertainty-aware" volume visualizations
 - Related work
 - Parametric models
- Our contributions
 - Nonparametric models
 - 2D transfer functions
- Results, conclusion, and future work





Ground truth



Mean



Nonparametric (proposed)



Parametric [Sakhaee and Entezari, 2017]



"Uncertainty-aware" Volume Visualizations

VIS2020



Uncertainty Visualization [Johnson and Sanderson, 2004]



Visualization pipeline [Brodlie et al., 2012]





Volume Rendering Uncertainty

- Volume visualization via mapping data and uncertainty into color and opacity dimensions of a transfer function, respectively [Djurcilov et al., 2002]
- Statistical quantifications vs. transfer functions for volume visualization [Kniss et al., 2005]
- Study of possible volume renderings via varying uncertain parameters of each stage of volume rendering pipeline [Fout and Ma, 2012]
- Effect of discretization errors on volume rendered images [Etiene et al., 2014, 2015]





Statistical Volume Rendering: Parametric Models [Sakhaee and Entezari, 2017]





Nonparametric Models of Uncertainty





Nonparametric Models of Uncertainty

Ground truth



Mean



One value per-voxel





Parametric

Nonparametric



Linear Interpolation of Random Variables

Linear interpolation of random variables represents the convolution of their probability distributions (for independent noise assumption) [Hogg et al., 2004]





[Sakhaee and Entezari, 2017; Feller, 1968]



Gaussian mixtures

✓IS2020



- Monte Carlo sampling of Gaussian mixtures [Liu et al., 2012]
- Image space compositing of Monte Carlo visualizations

Improved shape accuracy, but exponential complexity!

Quantile Interpolation [Read, 1999] for Nonparametric Distributions

- Object space compositing (No image space compositing)



Interpolation of the j'th quantile:

 $Pr(Q_j) =$



Closed-form linear time complexity framework (No Monte Carlo sampling, non-exponential framework)

Interpolated random variable



 $(1 - \alpha)Pr(Q_{2j}) + \alpha Pr(Q_{1j})$

Complexity linearly proportional to the number of quantiles







Quantile Interpolation

- Reconstruction of 2D uncertain vector fields [Hollister and Pang, 2013, 2015]
- paper for the proof)



• We propose reconstruction of 3D uncertain intensity field (refer to the

Probability distribution of interpolated random variable X using quantile interpolation in 3D



Our pipeline for Volume Rendering With **Nonparametric Statistics**





X

Integrate against transfer function



Expected fragment color computation: E(TF(x)) = $TF(x)Pdf_X(x)dx$









Statistical Volume Rendering: 2D Transfer Functions









Uncertain field [Sakhaee and Entezari, 2017] + 2D TFs [Kniss et al., 2001]



Results, conclusion, and future work

VIS2020



Tangle Function [Knoll et al., 2009] (Qualitative Comparisons)







Gaussian mixtures (four Gaussians) (Monte Carlo)

✓IS2020



(two quantiles)







Tangle function (Quantitative Comparisons)



RMSE = 0.0245fps = 10



RMSE = 0.0051



Gaussian mixtures (Monte Carlo)

VIS2020

RMSE = 0.0067fps = 6.1



Quantile interpolation (two quantiles)





Quantile interpolation (four quantiles)

RMSE = 0.0062fps = 4.9



Gaussian

RMSE = 0.0055fps = 5.3



Quantile interpolation (eight quantiles)

Tangle function (Quantitative Comparisons)



Ground truth

RMSE = 0.0245fps = 10



RMSE = 0.0067fps = 6.1

Quantile interpolation (two quantiles)

RMSE = 0.0051



Gaussian mixtures (Monte Carlo)





Number of Quantiles for Quantile Interpolation

Depends on sample size (#ensemble members), available memory, and computational power.











Quartile View: Uncertainty Visualization







(b) Central 50%, IQR

(c) Upper quartile

Teardrop Function [Knoll et al., 2009] (Qualitative Comparisons)







Teardrop Function [Knoll et al., 2009] (Quantitative Comparisons)









RMSE=0.003

Gaussian mixtures (Monte Carlo)

RMSE=0.001 Quantile interpolation (four quantiles) (eight quantiles)

[Proposed]



RMSE=0.001 Quantile interpolation



Red Sea Eddy Simulation Ensemble



Single member

TF

Courtesy: SciVis Contest 2020 dataset (https://kaust-vislab.github.io/SciVis2020/)

- Visualization of uncertain velocity magnitude field
- Confidence regarding the eddy presence/position: e₃: High
 - e₂: Moderate
 - e₁: Low



Uniform

Gaussian

Gaussian mixtures

Quantile Interpolation



Quartile View: Uncertainty Visualization



Confidence re presence/pos e₃: High e₂: Moderate e₁: Low



Osirix OBELIX Dataset

Analysis of the uncertainty due to downsampling of data



Ground truth

RMSE:0.0359



RMSE:0.0509



512x512x1559

Mean

64x64x195

Uniform



RMSE:0.0811



RMSE:0.0190



64x64x195

Gaussian mixtures (Monte Carlo)



Gaussian

Statistical Volume Rendering: 2D Transfer Functions

Gradient magnitude



Intensity

The tooth dataset





Mean



64x64x41





Parametric





Conclusion

- Closed-form nonparametric framework for efficient statistical rendering
- Quantile interpolation for reconstruction
- Qualitative and quantitative comparisons with the mean, parametric, and Gaussian mixture models
- Application of statistical volume rendering to 2D transfer functions





Future Work

- Uneven quantile values for quantile interpolation
- Multidimensional transfer functions (more than two dimensions) for nonparametric models
- Dependent random fields
- Optimal parameter estimation for noise models





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