

Procedural texture synthesis for zoom-independent visualization of multivariate data – supplemental material

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Appendix A: Intensity distribution of random-phase Gabor noise

The intensity distribution of n -dimensional random-phase Gabor noise can be closely approximated by the normal distribution with variance [LD11]:

$$\sigma_n^2 = \frac{\lambda}{2 \left(\sqrt{2}a \right)^n}. \quad (1)$$

Knowing this distribution allows us to construct a suitable noise transfer function. As we aim at maintaining the same number of impulses per cell regardless of the actual size of the cell, we can write that

$$\lambda = \frac{N \cdot \Gamma\left(\frac{n}{2} + 1\right)}{\pi^{\frac{n}{2}} G^n} \quad (2)$$

where λ is the impulse density, N is the desired number of impulses per truncated kernel volume, G is the size of the grid and Γ is the gamma function. Furthermore, we can write that

$$a = \frac{\sqrt{-\ln(t)/\pi}}{G} \quad (3)$$

where t is the level at which the Gabor kernel is truncated. Substituting equations 2 and 3 into Eq. 1 we find that

$$\sigma_n^2 = \frac{N \cdot \Gamma\left(\frac{n}{2} + 1\right)}{2^{\frac{n}{2}+1} \left(-\ln(t)\right)^{\frac{n}{2}}}. \quad (4)$$

Notice that the variance of the noise is independent of the size of the cell and only depends on the average number of impulses per truncated kernel volume and the level of truncation of the kernel. In two dimensions Eq. 4 reduces to $\sigma_n^2 = -N/4\ln(t)$.

Appendix B: Three-dimensional use-case

For the sake of simplicity of implementation, we employ the level-crossing probability (LCP) as presented in [PH11]. Although it overestimates the probabilities [PRW11, PWH11],

it is sufficient for our use case. We set the value for control of noise transfer function v_{tf} to the level-crossing probability, which is defined for normally distributed input data as:

$$v_{tf}(\mathbf{x}) = P_{\theta}(\mathbf{x}) = \frac{1}{2} \left(1 - \operatorname{erf} \left(\frac{\mu(\mathbf{x}) - \theta}{\sqrt{2}\sigma(\mathbf{x})} \right) \right), \quad (5)$$

where $\mu(\mathbf{x})$ and $\sigma(\mathbf{x})$ are the mean value and standard deviation of the value in the dataset at position \mathbf{x} . We use this value as an input to our noise transfer function, which results in a visualization, where the level-crossing probabilities can be perceived in the view-perpendicular directions (*i. e.*, along the silhouette of the isosurface). However, as the level-crossing probability normally takes all values between 0 and 1 along a ray crossing the surface, the LCP values would be very hard to read in a view-parallel direction. Therefore we propose to use the norm of the gradient of a stochastic distance function (SDF) [PRW11] to control the frequency of a 3D texture:

$$\Psi_{\theta}(\mathbf{x}) = \frac{\mu(\mathbf{x}) - \theta}{\max(\sigma(\mathbf{x}), \sigma_{min})} \quad (6)$$

where σ_{min} is a minimum standard deviation used to avoid numerical problems. We then map this value to $[0, 1]$ range by precomputing or interactively defining the maximum gradient norm value $\|\nabla\Psi_{\theta}\|_{max}$ and setting the frequency-controlling value v_{freq} to:

$$v_{freq}(\mathbf{x}) = 1 - \max \left(1, \frac{\|\nabla\Psi_{\theta}(\mathbf{x})\|}{\|\nabla\Psi_{\theta}\|_{max}} \right). \quad (7)$$

This results in lower noise texture frequency in the areas where SDF surfaces deviate further in space from the mean surface.

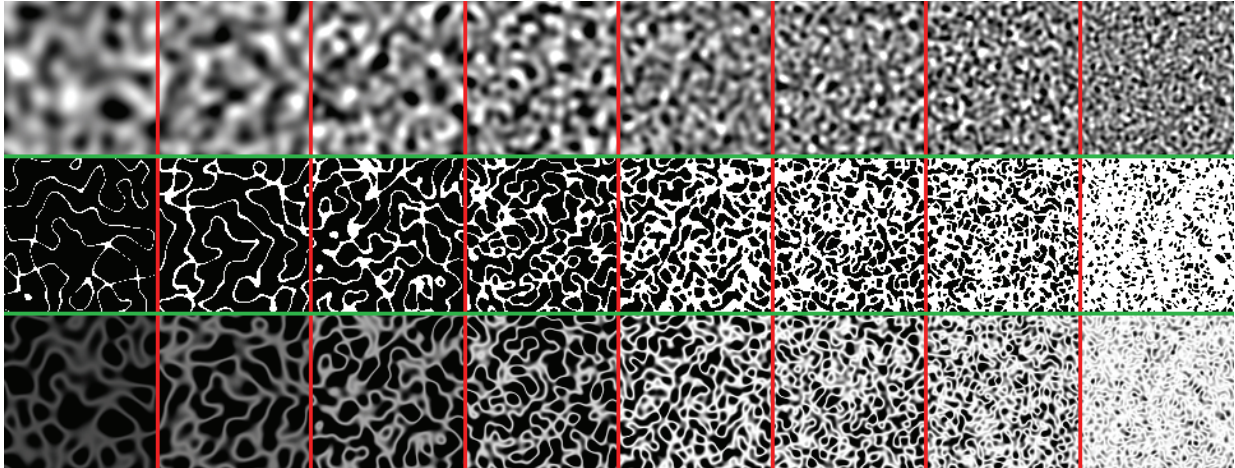


Figure 1: Comparison of effect of noise transfer functions. The value that is visualized changes from zero to one. Top: underlying noise without modifications. Middle: after application of step decay function. Bottom: After application of spline decay function. Please zoom in to see the details.

Appendix C: Full size images for print

This appendix contains the images from the main manuscript scaled to be of correct size when printed on A4 paper. The size of the printed images at distance of 35 centimeters will correspond to size of the images viewed on a screen with pixel size of 0.282 millimeters at distance of 60 centimeters (the intended viewing conditions these images were created for).

References

- [LD11] LAGAE A., DRETTAKIS G.: Filtering solid Gabor noise. In *ACM SIGGRAPH 2011 papers* (2011), SIGGRAPH '11, ACM, pp. 51:1–51:6. [1](#)
- [Mil07] MILLER J. R.: Attribute blocks: Visualizing multiple continuously defined attributes. *IEEE Computer Graphics and Applications* 27 (2007), 57–69. [9](#)
- [PH11] PÖTHKOW K., HEGE H.-C.: Positional uncertainty of isocontours: Condition analysis and probabilistic measures. *IEEE Transactions on Visualization and Computer Graphics* 17, 10 (2011), 1393–1406. [1](#)
- [PRW11] PFAFFELMOSE T., REITINGER M., WESTERMANN R.: Visualizing the positional and geometrical variability of iso-surfaces in uncertain scalar fields. *Computer Graphics Forum* 30, 3 (2011), 951–960. [1](#)
- [PWH11] PÖTHKOW K., WEBER B., HEGE H.-C.: Probabilistic marching cubes. *Comput. Graph. Forum* 30, 3 (2011), 931–940. [1](#)
- [VMFS11] VEAS E. E., MENDEZ E., FEINER S. K., SCHMALSTIEG D.: Directing attention and influencing memory with visual saliency modulation. In *Proceedings of the 2011 annual conference on Human factors in computing systems* (2011), CHI '11, ACM, pp. 1471–1480. [3](#)

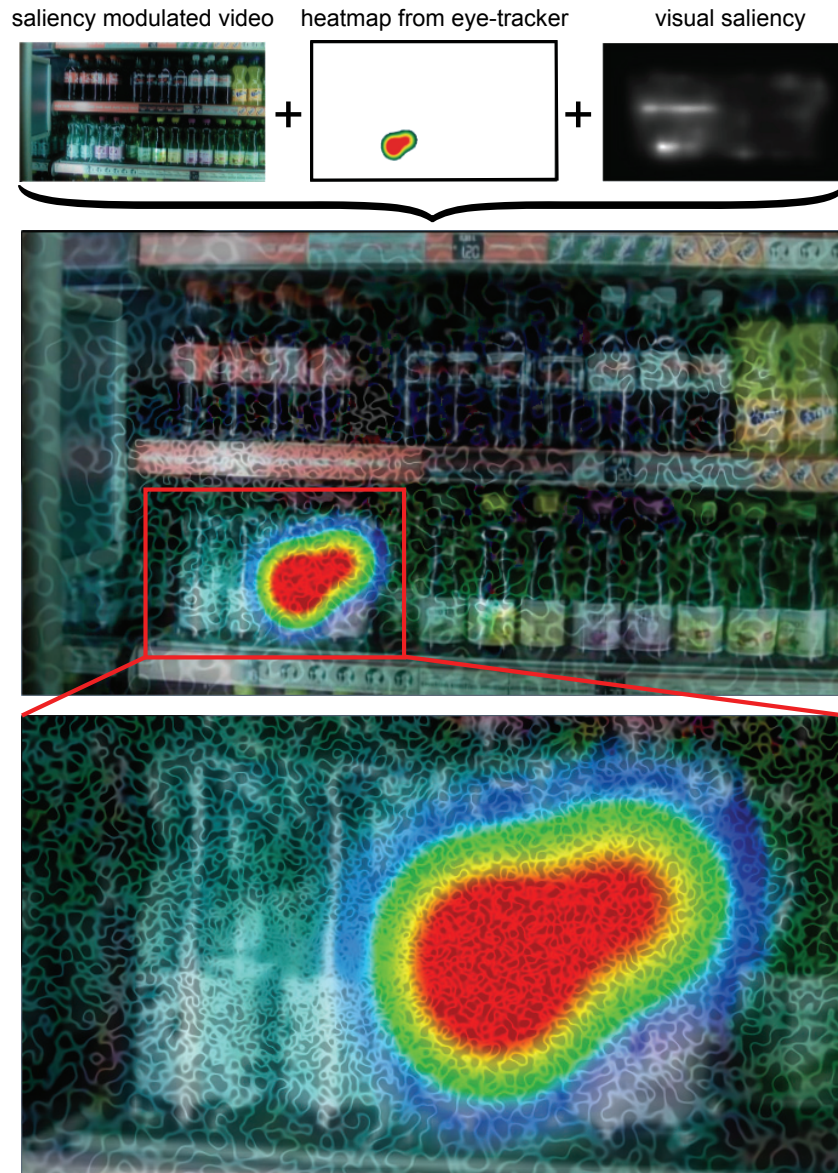


Figure 2: This figure shows our approach during the analysis of an eye-tracker experiment with visual saliency modulated videos [VMFS11]. The amount visual saliency is visualized as texture frequency and pattern thickness. Highly salient regions are encoded with thick lines and high frequency. Concurrently, we show the time the user looked at a specific region with a color-coded heatmap.

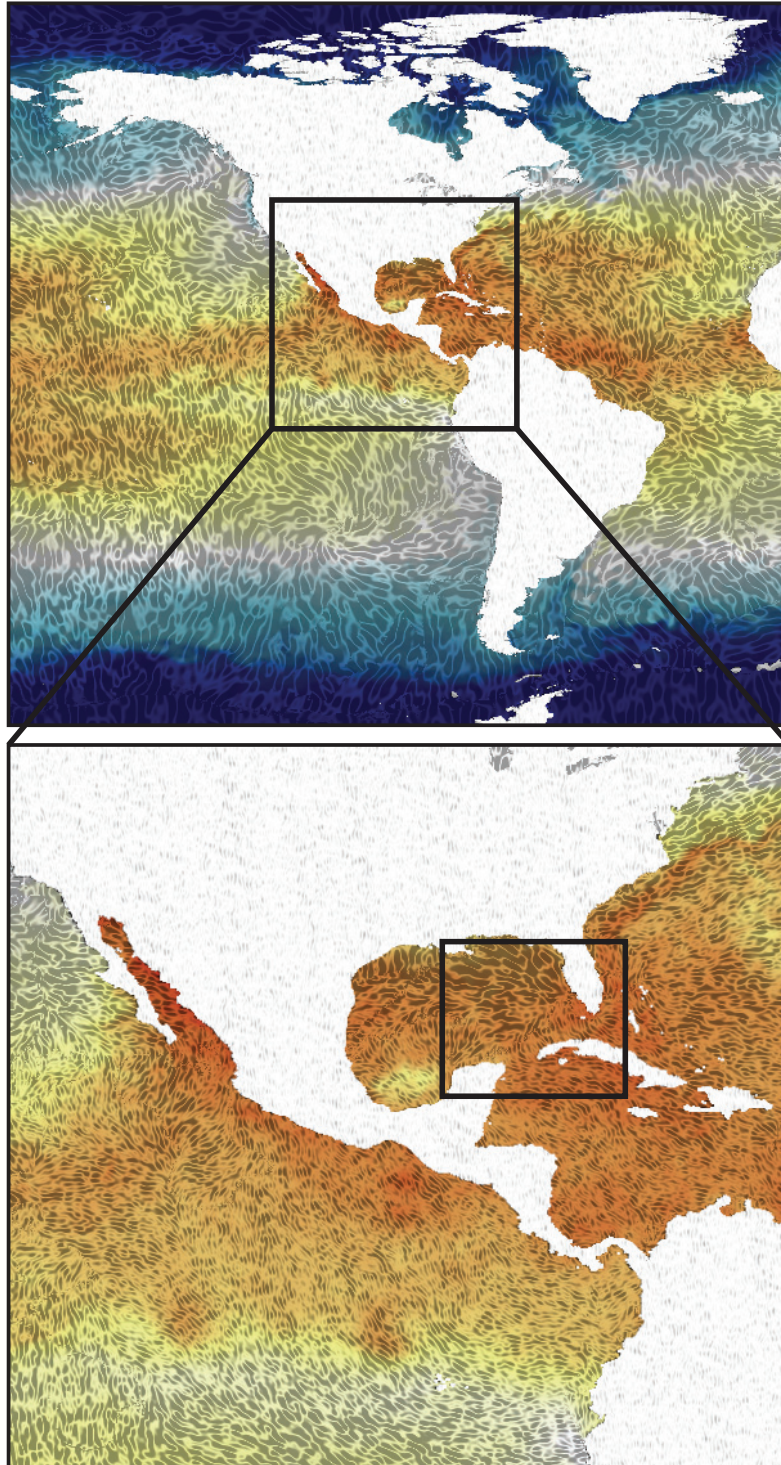


Figure 3: The shown world map color codes the average sea temperature from 14th of September 2011. On top, the procedural noise encodes the amount of precipitation (noise frequency and pattern thickness) with the optical flow of the precipitation between 14th and 15th of September 2011 (texture orientation). Encoding the optical-flow value between two points in time as second visualization channel, allows the user to estimate the evolution of the precipitation value as well. Note the increasing amount of details with increasing zoom level. Continued in Figure 4.

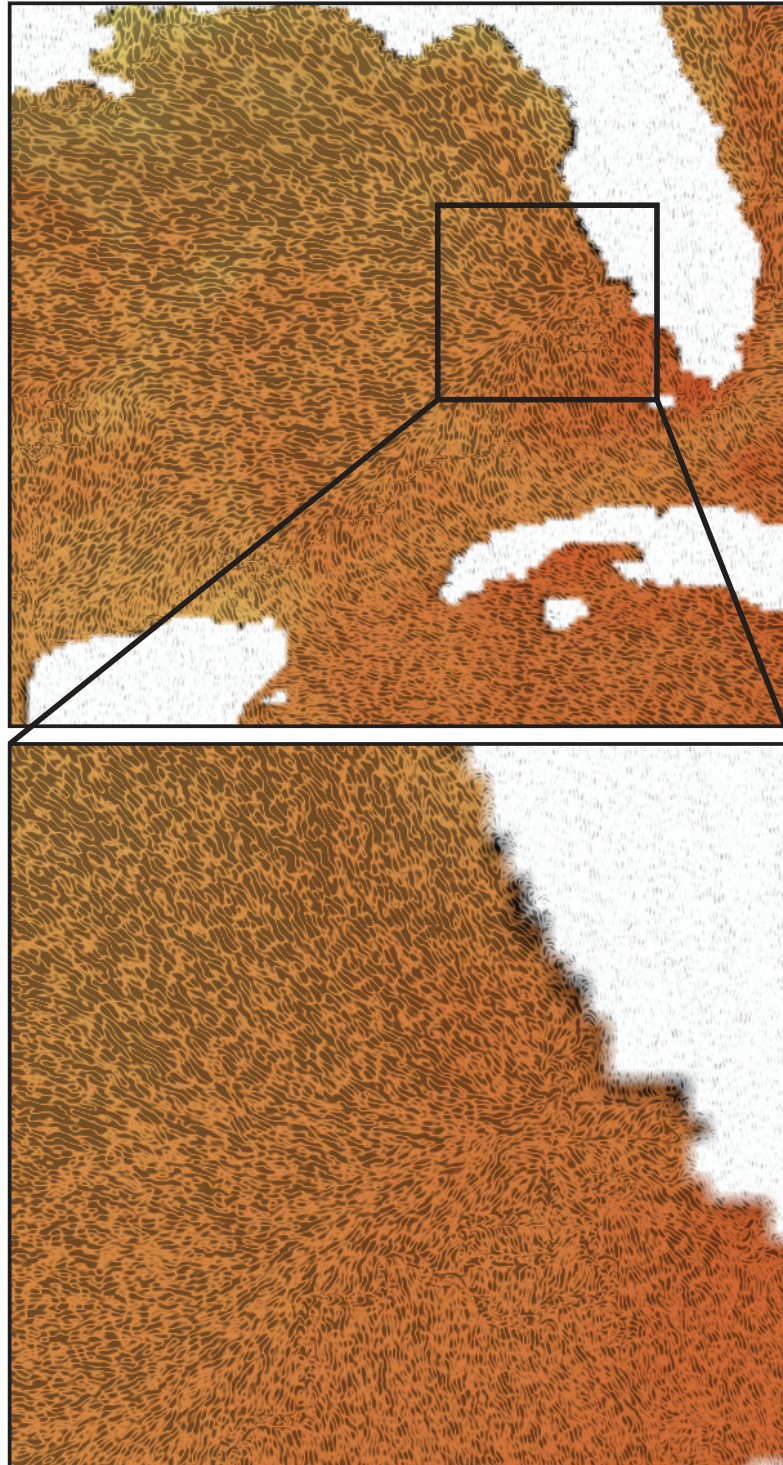


Figure 4: Continued from Figure 3. The shown world map color codes the average sea temperature from 14th of September 2011. On top, the procedural noise encodes the amount of precipitation (noise frequency and pattern thickness) with the optical flow of the precipitation between 14th and 15th of September 2011 (texture orientation). Encoding the optical-flow value between two points in time as second visualization channel, allows the user to estimate the evolution of the precipitation value as well. Note the increasing amount of details with increasing zoom level.

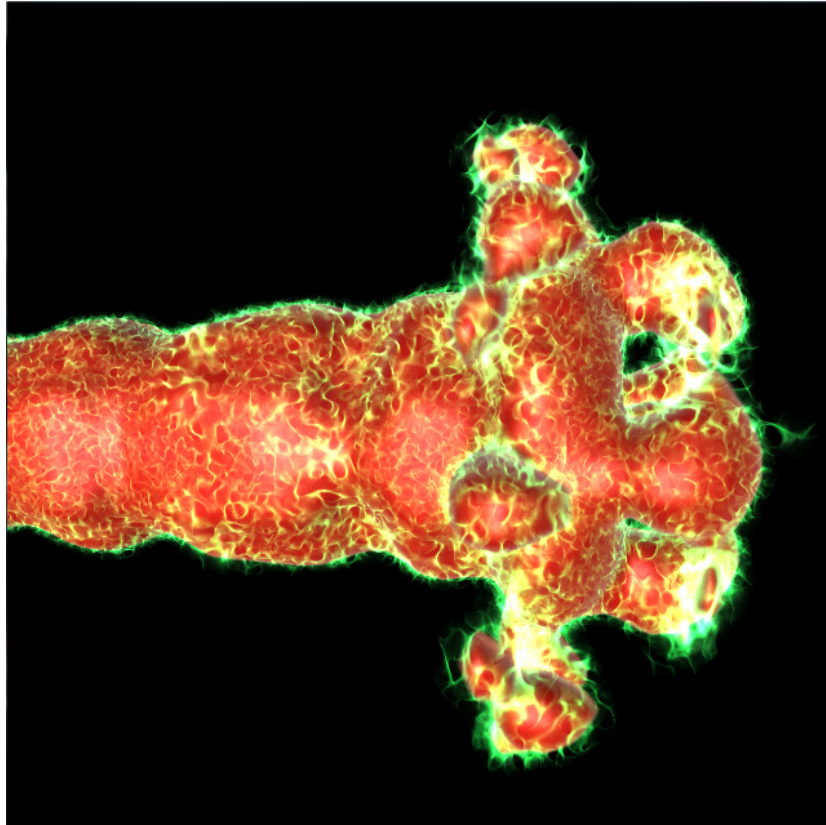


Figure 5: Several views of 3D visualization of isocontour uncertainty of the Fuel dataset using our visualization method. The noise transfer function uses level-crossing probability as its input and the texture frequency shows the norm of the gradient of the stochastic distance function, with higher frequencies corresponding to lower gradient norm values, meaning that the position of the isosurface is more uncertain.

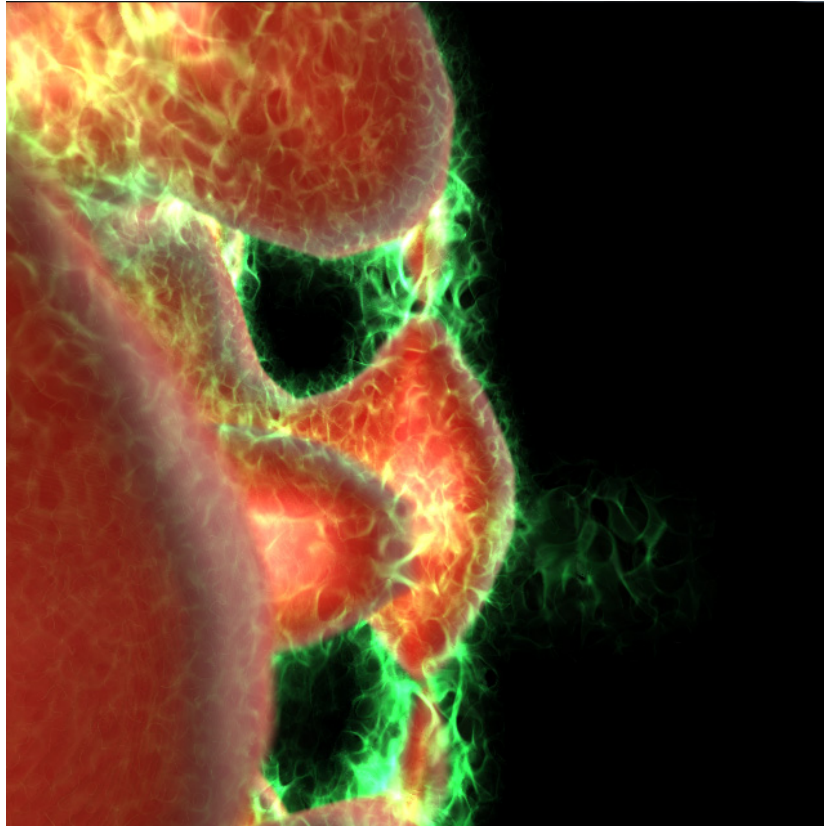


Figure 6: Several views of 3D visualization of isocontour uncertainty of the Fuel dataset using our visualization method. The noise transfer function uses level-crossing probability as its input and the texture frequency shows the norm of the gradient of the stochastic distance function, with higher frequencies corresponding to lower gradient norm values, meaning that the position of the isosurface is more uncertain.

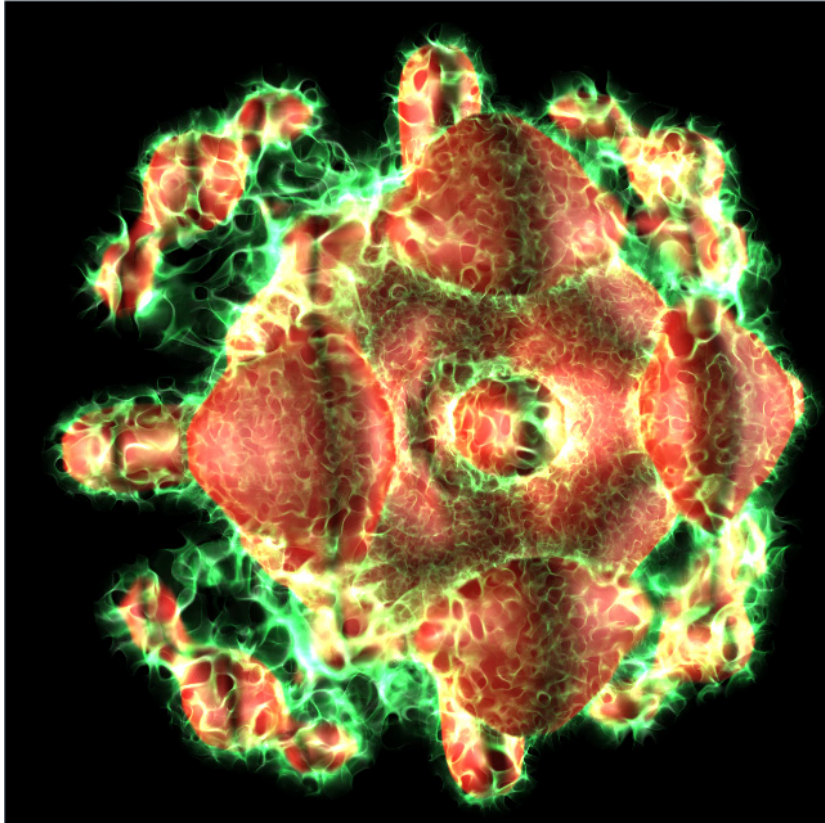


Figure 7: Several views of 3D visualization of isocontour uncertainty of the Fuel dataset using our visualization method. The noise transfer function uses level-crossing probability as its input and the texture frequency shows the norm of the gradient of the stochastic distance function, with higher frequencies corresponding to lower gradient norm values, meaning that the position of the isosurface is more uncertain.

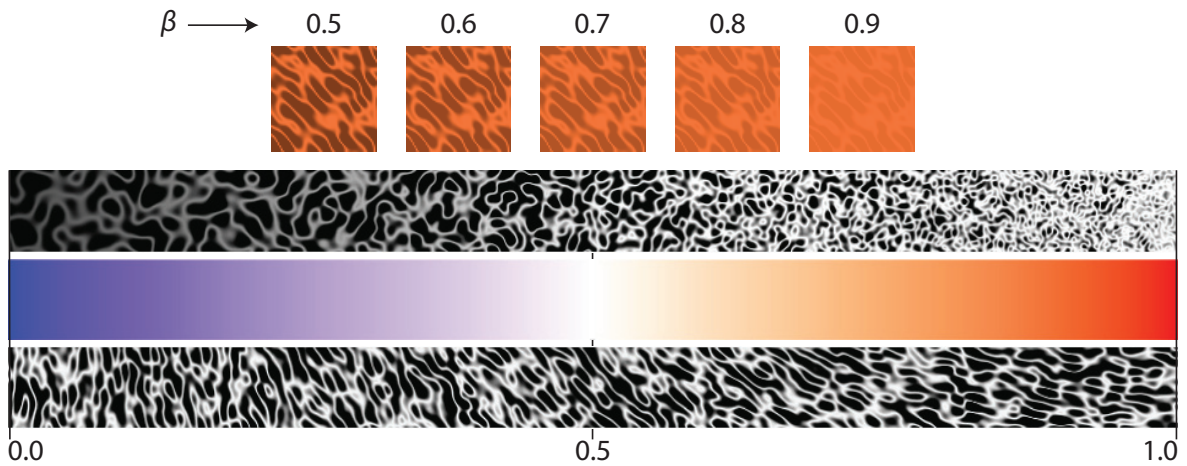


Figure 8: 1st row: an example data triple (0.521, 0.633, 0.312) for the five tested β values. 2nd, 3rd, 4th rows: the legend for our method that was used in both our user studies.

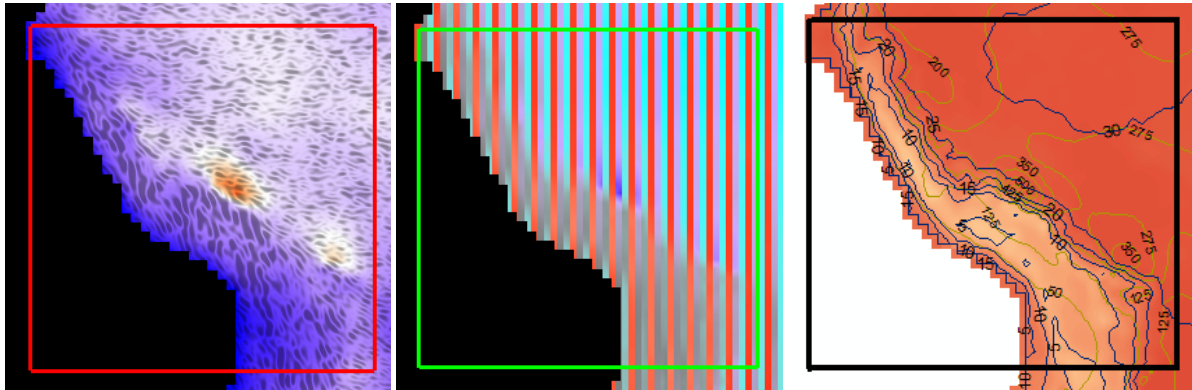


Figure 9: Examples of visualizations compared in our user study (from left to right): our method (noise-based texture), attribute blocks [Mil07], labeled contours (produced with ArcGIS®10 software).