Pulsating Uncertainties: Visualization and Highlighting of Uncertainty in 3D Data Using Animated 2D Transfer Functions

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Abstract: While data with uncertainties arises in many scientific domains and engineering applications, the visualization of such data remains challenging as uncertainty information must be included in an accessible and comprehensible manner.In this paper we present *pulsating uncertainties* as a novel way to highlight uncertainties by animated two-dimensional transfer functions (2DTF) for uncertain scalar data sets. It allows for a flexible classification by 2DTFs and an effective and pre-attentive highlighting of uncertainty by animating the 2DTFs while enabling users to simultaneously explore the 3D scene.In addition, we present the *isosurface variability widget* to highlight the variability of isosurfaces for data with uncertainty.We demonstrate the characteristics of the new approach by experiments using climate simulation and medical data.

1 INTRODUCTION

Direct volume rendering (DVR) is a common visualization method to explore and visualize volumetric data sets emerging in medicine, engineering and natural sciences. Due to a lack of precise measurements, a lack of prediction accuracy, a lack of completeness, to name only a few examples (Kamal et al., 2021), such data can be affected by uncertainty. Thus, almost all types of visualization methods, among them DVR, have been adapted or extended to be able to deal with uncertainty (e.g. (Athawale et al., 2021; Sakhaee and Entezari, 2017; Liu et al., 2012)) or to allow visualizing the uncertainty in the data to some extent (Pang et al., 1997; Bonneau et al., 2014; Hägele et al., 2022). The latter is especially important for those users who want to understand, analyze or at least consider the uncertainty in the data they are working with. In this paper, we present *pulsating uncertainties*, a novel DVR approach combining animation and two-dimensional transfer functions (2DTFs) in order to pre-attentively highlight more uncertain areas in the dataset and to automate the exploration and illustration of these areas. This deliberately contrasts with numerous state-of-the-art methods that employ transparency to illustrate uncertainty and thus rather hide data points with higher uncertainty instead of highlighting them.

Our approach addresses and solves four tasks (H_i) focus on highlighting the uncertainty and two tasks (I_i) focus on assisting users in the interactive exploration in the context of DVR-based visualization of uncertainty in 3D scalar fields which have not been addressed in previous work: $\mathbf{H_1}$ As uncertainties in the data often require special attention, regions with higher uncertainty should be highlighted to enable their intuitive and *pre-attentive* identification. $\mathbf{H_2}$ Isosurfaces are one of the prevalent visualization methods for 3D scalar data, and prior research has explored their application in uncertain datasets (Pöthkow and Hege, 2011; Pöthkow et al., 2011; Pfaffelmoser et al., 2011). As the position of the surfaces is unsure, their possible distributions should be illustrated in a way that allows to be recognized *pre-attentively*. $\mathbf{I_1}$ The *pre-attentive* highlighting of the uncertainty should be retained, while allowing users to manually explore the three-dimensional scene by manipulating the view (rotate, pan, scale). $\mathbf{I_2}$ Allow for an automated exploration of the data values (e.g. mean) for specific uncertainty ranges, while allowing users to manually explore the three-dimensional scene. *Pulsating uncertainties* support these tasks using a combination of 2DTFs, animations and a specific 2DTF widget which

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we call *isosurface variability widget* (IVW).

We do not aim to replace well-established DVR-based uncertainty visualization techniques by *pulsating uncertainties*, but rather see our approach as a complementary technique in cases where existing techniques are tedious to use or do not sufficiently guide the attention of the users to the uncertainty in the data. We note that our method is aimed at uncertainty present in the data itself (*data uncertainty* (Kamal et al., 2021)) and does not treat uncertainty resulting from the visualization process or being propagated through the pipeline (*visualization uncertainty*).

2 RELATED WORK

As mentioned above, many methods for the visualization of uncertainty have been proposed in the last decades. Surveys by Kamal et al. (Kamal et al., 2021), Pang et al. (Pang et al., 1997) and Bonneau et al. (Bonneau et al., 2014) summarize this work. While past work includes techniques for many different types of data, we concentrate on methods dealing with scalar fields. More specifically, our method is related to work in the three areas:

a) visualization of scalar fields with uncertainty,

b) direct volume rendering and transfer functions (especially two-dimensional transfer functions), and

c) visualizations employing animations.

In the following, we summarize the related work in sections considering different combinations of the above listed areas.

Visualization of Uncertainty of Scalar Fields Including DVR and transfer functions (TFs). [a+b] One of the earlier works regarding the visualization of uncertainty in scalar fields using DVR has been presented by Djurcilov et al. (Djurcilov et al., 2002). While Djurcilov et al. use predefined colored regions on a scatter plot to specify a 2DTF for the volume rendering, the approach we propose uses an interactive 2DTF editor with different widgets and color-scales to classify regions of interest. Other work, e.g. Sakhaee et al. (Sakhaee and Entezari, 2017) and Athawale et al. (Athawale et al., 2021), included the uncertainty into the volume rendering process itself, allowing to explore volumetric data with uncertainty using probability density functions (PDFs) and non-parametric representations. None of these works however considers the effect of animations applied to 2DTF classification widgets in the context of uncertainty visualization of scalar fields.

Visualization of Uncertainty of Scalar Fields Using Animations. [a+c] Gershon (Gershon, 1992) proposed one of the few approaches to visualize uncertainty, here fuzziness, using animation. Later, Ehlschlaeger et al. (Ehlschlaeger et al., 1997) look into the visualization of positional uncertainty in elevation models using an animation-based sequence of possible surface realizations. Brown (Brown, 2004) introduced a new approach for visualizing uncertainty using animated visual vibrations through oscillation functions.

Our approach follows these works in targeting human motion perception to highlight areas with higher uncertainty using DVR and pulsating 2DTFs to visualize the volume data directly while integrating uncertainty information into the rendering.

Visualization with DVR and TFs Including Animations. [b+c] Correa et al. (Correa and Silver, 2005) present a method for data set traversal by moving a region in which a TF is applied along a pre-specified skeleton path in order to provide focus-plus-context (F+C) views. Another F+C visualization approach has been introduced by Woodring et al. (Woodring and Shen, 2007), proposing the concept of animating TFs to incorporate animations in volume rendering. Yet another work presenting F+C visualization has been presented by Sikachev et al. (Sikachev et al., 2010) extending towards a dynamic F+C approach that highlights features during user interaction. Akiba et al. (Akiba et al., 2010) presented *AniViz*, an animation tool which allows a user to turn the results of data exploration and visualization into an animation.

While the aforementioned works give insights about the application of animations in a volume rendering context, this article uses animations of 2DTFs to investigate their effect with regard to the visualization of uncertainty in a spatial data set.

Visualization of Uncertainty with DVR and TFs Including Animations. [a+b+c] The work of Lundström et al. (Lundström et al., 2007) is the only one found related to the investigation of uncertainty (a) using animations (c) with DVR and TFs (b). In their approach, they address the uncertainty *in the classification* of a TF by interpreting overlapping classifications to be uncertain. These fuzzy classifications are presented as an animated rendering of the mapped color/opacity. In comparison to Lundström et al. who investigate the visualization of uncertainty stemming from the classification, our approach focuses on the uncertainty in the scalar data using animated 2DTFs for DVR thus resulting in a different presentations and implementations.

Others. While not directly related to our approach, Pöthkow et al. (Pöthkow and Hege, 2011) and Pfaffelmoser et al. (Pfaffelmoser et al., 2011) presented approaches to visualize the positional variability of isosurfaces in uncertain scalar fields, to which we achieve comparable results with a special application case based on task H_2.

Other authors aimed to incorporate the data uncertainty into the pipeline stages of DVR (Athawale et al., 2021; Sakhaee and Entezari, 2017; Liu et al., 2012). This allows them to preserve the classical, non-uncertain TF while uncertain data is present. In contrast to our work, this approach yields visualizations in which it is impossible to discern the extent of accumulated uncertainty in the resulting visualization. In other words, the uncertainty of the data is not mapped directly to visual properties which allow identifying areas of high uncertainty.

3 WIDGETS, MAPS & ANIMATIONS FOR 2DTFs FOR UNCERTAINTY

The approach for uncertainty visualization proposed in this article is based on a set of visualization-related features that are applied in the context of a 2DTF-editor. These features are: (i) the use of different shapes for classification widgets; (ii) color and opacity maps applied to classification widgets; and (iii) widget animations inside the 2DTF-editor.

The combination of the features in different ways results in the ability to create visualizations of scalar volume data with uncertainty enabling the fulfillment of the tasks presented in the introduction of this article. However, the combination of these features imply issues, which we address in separate subsections. The baseline of our approach lies in the integration of Djurcilov et al. (Djurcilov et al., 2002) concept of using 2DTFs for uncertainty visualization into a basic 2DTF-editor like the one presented by Kniss et al. (Kniss et al., 2002) and animate the widgets to create a highlighting mechanism.

Let a scalar field with uncertainty $\mathbf{X}$ be given in $\mathbb{R}^3$ with the data at each point i being modeled by a Gaussian normal distribution $X_i \sim \mathcal{N}(\mu_i, \sigma_i^2)$ with mean μ_i and variance σ_i^2. A 2DTF-setup that presents the baseline can be seen in Figure 1 where mean μ and standard deviation σ are used for the two dimensions of the 2D-histogram, which depicts the frequency of value pairs in the data set. The x-axis (horizontal) of the histogram represents the value range of the mean values, while the range of standard deviation values are presented on the y-axis (vertical). Due to this setup, classification widgets in the editor, like the red widget in Figure 1, can be used to facilitate a classification of data with uncertainty. The advantage of

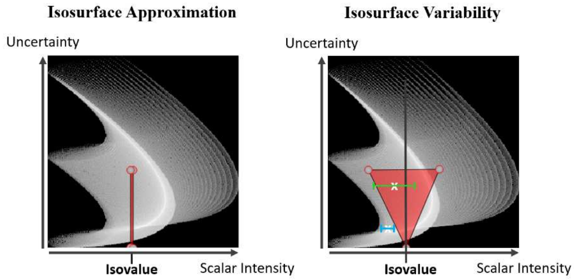

Figure 1: Left: Approximation of an isosurface using a rectangular widget. Right: Classification of the isosurface variability using a triangular IVW. While the left 2DTF includes only value pairs that are very close to the isovalue, the IVW includes value pairs that are further away but *might* be close to the isovalue due to uncertainty. Two horizontal bars (in blue or green) exemplify the value range of two points (white cross) with a different standard deviation.

this setup is the implicit interpolation of Gaussian distributions using the *Gaussian PDF interpolation* in which the mean and the standard deviation are interpolated separately (Pöthkow and Hege, 2011).

The combined application of the features listed above present a toolkit for visualizing the uncertainty in spatially distributed scalar data. The following subsections discuss the possible effects which each of these features has on the final visualization.

3.1 Classification and Widgets

In the context of 2DTF editors, classifications are achieved by manipulating widgets inside the GUI. Although other widget shapes could be easily added to our implementation, we use only two basic widget shapes for uncertainty visualization: rectangles and triangles (see Figure 1). Complex classifications can be composed of multiple of these basic widgets.

Isosurface Variability Widget (IVW). As the dimension in our 2DTFs represent the mean and the uncertainty an upside-down isosceles triangle widget can be used to show the variability of an isosurface. We call this an *isosurface variability widget* (IVW). An example of the IVW is shown in Figure 1 (right). Here, the isovalue is defined by the apex of the triangle and thus by its center. Since points higher in the 2D histogram have a higher uncertainty, the IVW effectively includes more value pairs that have a certain probability to actually exhibit the isovalue. This is illustrated in Figure 1 for two points represented as white crosses. The standard deviations of these points are represented by the green and the blue bar. Kniss et al. use a similar widget for isosurface visualization (Kniss et al., 2002).

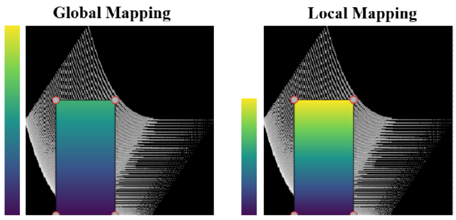

Figure 2: Widgets using global and local colormapping.

We can define the width $w(\sigma)$ of the IVW using a *confidence interval* γ. For Gaussian distributed variables the probability γ, that a value θ is within the interval of z times the standard deviation σ around the mean μ is as follows:

$$\gamma = P(\mu - z\sigma \leq \theta \leq \mu + z\sigma) = erf\left(\frac{z}{\sqrt{2}}\right), \quad (1)$$

while $erf(x)$ is the error function. We can solve Equation 1 for the z times of a standard deviation in order to identify the width w of the IVW:

$$z(\gamma) = \sqrt{2}\, erf^{-1}(\gamma), \quad (2)$$

where erf^{-1} is the inverse of the error function. Now, we can adjust the width $w_\gamma(\sigma) = 2z(\gamma)\sigma$ of the IVW, based on the standard deviation σ to ensure that $\gamma\%$ of the possible positions of the isosurface are visualized. The linearity of $w_\gamma(\sigma)$ with respect to σ shows that the triangle with its straight edges is the perfect shape for the IVW.

3.2 Colormapping

To apply color maps and opacity maps to enable the differentiation of values inside scalar data is a common practice in the field of data visualization. Opacity as a visual variable has also been used in the context of 2DTFs (Djurcilov et al., 2002) and 2DTF editors (Kniss et al., 2002). In our approach we apply color maps with different orientations (Fig. 2 vs. Fig. 6) to classification widgets in a 2DTF-editor to enable the differentiation of values of either the scalar field or the uncertainty field in the 2DTF-setup.

To enhance visual distinctness in the rendering, we employ two mapping states for widgets: *global* and *local* mapping, as illustrated in Figure 2. *Global* mapping uses the entire value range of the dataset for color assignment, while *local* mapping limits the color map to the value range classified by the widget's dimensions, improving clarity for specific value ranges of interest. Unlike *global* mapping, *local* mapping is influenced by widget size changes and animations, which are discussed further in the next section.

3.3 Animation

As mentioned, DVR animations have been used for exploratory tasks and focus+context views of features in scalar *volume* data (Woodring and Shen, 2007), and animating possible *surface* realizations (Brown, 2004; Ehlschlaeger et al., 1997) has been used for *uncertainty* visualization. Going beyond these works, we integrate animations into the process of *uncertainty* visualization of *volume* data by animating the 2DTF-classification itself. More specifically, we apply scaling animations to differently shaped and colormapped classification widgets in a 2DTF-editor. Some of the possible advantages of scaling widget animations with regard to uncertainty visualization include: a) Automated exploration (no manual interaction necessary), b) increased comprehensibility of the connection between rendering and 2DTF, c) visualization of change in the data domain, d) focus+context highlighting views with animated and static classification widgets and e) fading in and out of more uncertain or certain regions.

Using 2DTFs editors typically requires manual focus on creating classifications with widgets. Introducing widget animations enables automated data exploration with consistent speed, overcoming the imprecision of manual exploration. For scaling animations, this facilitates automated exploration of the scalar field represented by the x or y axis in the scatter plot. Figure 3 illustrates how scaling animations progressively include or exclude value pairs based on metrics like mean or standard deviation, rendering areas with higher uncertainty increasingly transparent and invisible.

Animations enable the perception of data domain changes linked to the direction of scaling, such as large volume regions becoming transparent or visible, highlighting the frequency of specific value pairs. Additionally, widget animations aid in forming a semantic connection between the 2DTF classification and the visualization (Kniss et al., 2002).

As mentioned, we defined two colormapping states for the widgets. While *global* mapping directly leads to expected results when applying animations to colormapped widgets, *local* mapping is not straightforward in the context of animations. This is due to the fact, that for *local* colormapping, the color scale is applied based on the size of the widget. To avoid unintended color/opacity changes in the rendering, we introduce an anchoring mechanism. With this, when a colormapped widget using *local* mapping is animated, the color scale is always applied to the initial size of the widget (Figure 2 and Figure 3).

3.4 Implementation

Naive approaches to animated TFs involved updating and uploading the 2D TF texture to the GPU, causing performance issues. To address this, we extended the 2D TF texture into a 3D texture, using the third dimension to store animation steps. This allows GPU-based DVR animation through simple frame lookups, with Θ as the total frames and T as the animation duration. A slice $\theta \in [0, \Theta - 1]$ of the 3D texture represents the state of the animation at time $t(\theta) = \frac{T}{\Theta}\theta$. Figure 4 illustrates this approach for the animation in Figure 3. Each horizontal, semitransparent slice of the 3D texture is shown separately for the first half of the cyclic bouncing animation. Please note, in this figure, white areas represent a material color with zero opacity and the start frame is the most bottom one.

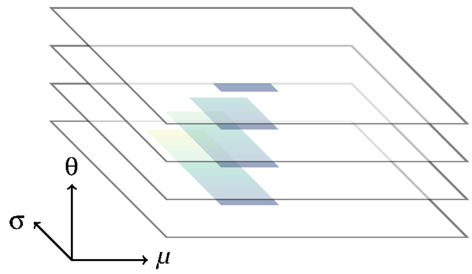

Figure 4: Illustration of the 3D texture of the first half of the cyclic bouncing animation. Each frame θ is shown as a semitransparent 2D slice.

4 RESULTS

To showcase our uncertainty visualization approach, we applied it using various 2DTF setups to address previously outlined tasks. The approach was prototyped in an open-source tool with modules for DVR, extended to support colormapping and widget animations. All renderings and accompanying videos were produced on a system with an AMD Ryzen 7 3700X CPU and NVIDIA GeForce RTX 4060 Ti GPU.

4.1 Data Sets

Here, we introduce the data sets we use to illustrate our results for the different tasks. If not noted otherwise, the data is given on a regular grid and the values at the points are defined as Gaussian random variables. At first, to achieve a more analytically comprehensible visualizations we use the well known **tangle** function (Knoll et al., 2009) (see also Figure 5). Similar to Athawale et al. (Athawale et al., 2021) the tangle function is mixed with noise to generate an ensemble representing uncertain data using a resolution of 512^3.

To demonstrate the effects of our approach on medical data, we use **CT data** taken from the CHAOS (combined [CT-MR] healthy abdominal organ segmentation) challenge (Kavur et al., 2019). We used the registered CT data of 20 patients to compute the weighted mean and variance. The resulting three-dimensional scalar field with uncertainty has a resolution of $256 \times 256 \times 81$. Due to physical differences of patients in this data set, we have to weight the first patient 20 times more than the other 19 patients. Otherwise, the mean and variance of the created scalar field with uncertainty would not look valid.

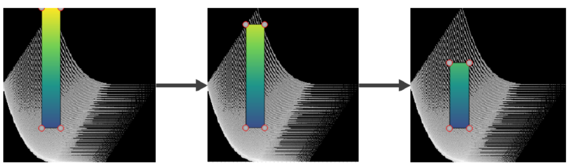

Figure 3: Frames of scaling animation applied a colormapped widget. When the top of the widget moves down samples with higher uncertainty are rendered transparent.

We also demonstrate the use of animated 2DTFs on the climate ensemble of the **DEMETER** project (Palmer et al., 2004). This ensemble contains the daily average hindcast for the temperature for February 20^{th}, 2000. The data is generated by seven climate models, where each model produced nine sets with distinct simulation parameters. We used mean and variance of the 63 ensemble members to model the scalar field with uncertainty ($144 \times 73 \times 4$).

4.2 User Interaction and Highlighting (Task I_1)

In our first experiment, we address task I_1 to explore the uncertainty of the tangle function. Figure 5 shows DVR and 2DTF for three frames, where scaling down the 2DTF progressively excludes points with higher uncertainty, leaving only those with low mean and low standard deviation. This simple example highlights automated uncertainty exploration for a fixed mean range, enabling users to interactively examine 3D structures while benefiting from the automation.

4.3 Automated Exploration of Mean for an Uncertainty Range (Task I_2)

Our second experiment addresses task I_2 for the tangle data, focusing on exploring regions with low uncertainty. Using the 2DTF setup in Fig. 6, animating the widget to narrow its width highlights low-valued points. This automated exploration allows users to investigate features by rotating the visualization or zooming into interesting regions, as shown in Fig. 6.

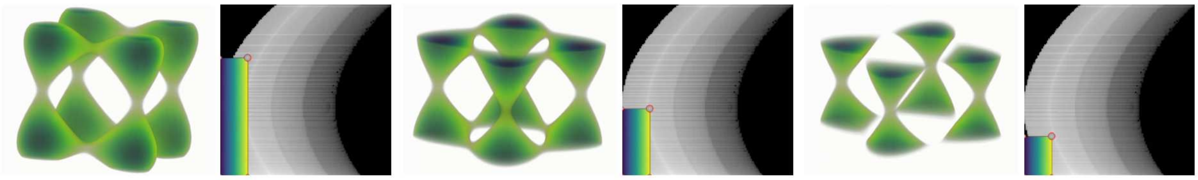

Figure 5: Using color map and animation: basic visualization of increasingly hiding more uncertain areas in the data. This leads to the highlighting of uncertainty while allowing manipulating the view for manual exploration as described by task I_1.

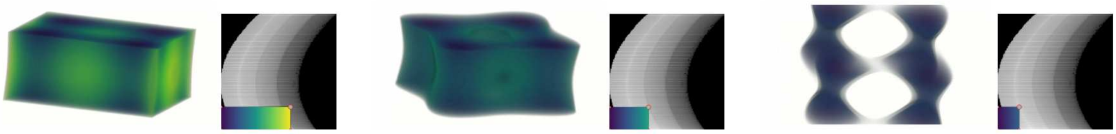

Figure 6: Frames of an animation where the values of the mean field are explored for a specific uncertainty range (Task I_2). The 2DTF-setup uses a rectangular widget with a local colormap in x-direction to enable visual differentiation of the selected mean values. From left to right the renderings vary in the width of 2DTF widget. Additionally, the later renderings were interactively rotated during the animation process. Note that between the left and the middle rendering only small changes occur, but the related 2DTF classification widget is already at half its initial size. This illustrated the distribution or rate of change of mean values throughout the volume dataset..

4.4 Pre-Attentive Highlighting of Uncertainty (Task H_1)

This experiment demonstrates the application of pulsating animations of the CT data set in order to highlight regions with higher uncertainty. The pulsation allows the intuitive and *pre-attentive* identification of the uncertainties in the data. The used 2DTF setup is shown in the insets in Figure 7 alongside with the resulting rendering. To create a static context, a gray rectangle widget is used to show points in a narrow range of mean values with comparatively low uncertainty. An additional rectangle widget colored in magenta is used to show points with higher uncertainties. This leads to an initial rendering, where more certain values are rendered gray, while areas of higher uncertainty are prominently visualized using magenta. To repeatedly fade the uncertain areas in and out, a scaling animation is applied to the widget, so that its top moves down. The effect of this is visible in the frames shown in Fig. 7. Due to the fading of uncertain areas viewers are increasingly presented with more certain areas defined by the initial 2DTF-setup. Areas with highly uncertain values are highlighted by the pulsating animation and can be pre-attentively identified.

In this case, when comparing the left and the right rendering, it can be seen that most areas belonging to the rib cage possess a higher uncertainty as they are close to invisible in the right rendering showing the more certain areas. Djurcilov et al. (Djurcilov et al., 2002) used opacity in this way to highlight uncertain areas. However, this prevents opacity from being used as a way to create feature related contexts in the classification step of the DVR pipeline. For this reason, we use color as the primary visual variable and animation as supporting visual cue to convey uncertainty to the viewer while using opacity to reduce occlusion. This can also be seen in the renderings of Figure 7, where due to a lower opacity of the static context visualization it is possible to perceive areas with higher uncertainty that lie *inside* the shown context regions.

4.5 Visualizing the Variability of an Isosurface (Task H_2)

To address task H_2 we animate the IVW (Section 3) and thus continuously fade (in/out) the less probable isosurface realizations. Figure 8 shows this approach applied to the climate data set. The initial 2DTF-setup and rendering can be seen on the left, while the other renderings and 2DTFs present a progressed state of the animation horizontally collapsing the IVW. Here, the mean isovalue of 273.15 K (0° C) has been used. The entire animation cycle, which also expands the IVW, can be seen in the video accompanying this article. The effect of this widget animation is a progressive elimination of positions that are most uncertain to actually be part of the isosurface. Thus, initially, the visualized region represents potential realizations of the isosurface for 0° C. Later, e.g. in the third rendering, only more probable realizations are shown.

Note that the thickness of the rendered region at a specific location can be an indicator of the uncertainty or the gradient magnitude of the data. High uncertainty results in a thicker "surface" because points with very different mean values can be part of the isosurface; lower gradient magnitude results in a thicker "surface" because similar mean values are spread out over a larger area. In Figure 8, this is most apparent in

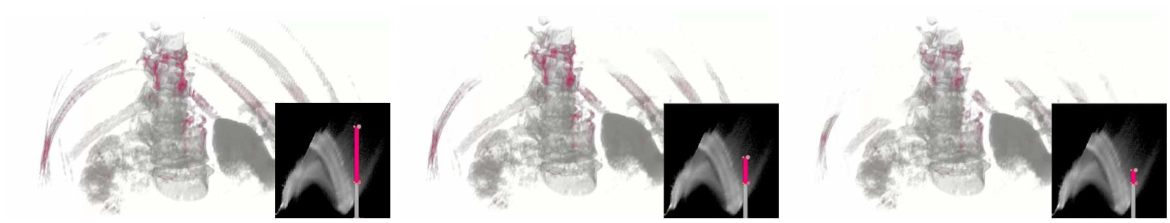

Figure 7: Frames of a 2DTF-animation for CT dataset. The 2DTF-setup enables fading in/out of areas with higher uncertainty, while also maintaining a static visualization of the more certain structural context represented by the grayish areas. This results in an example of how task H_1 can be performed regarding the visualization of uncertainty in the respective dataset.

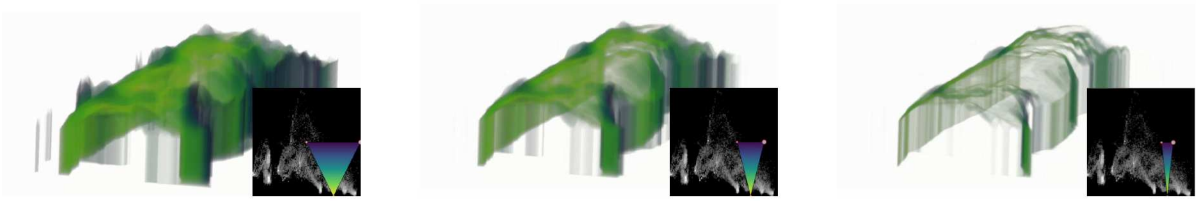

Figure 8: DVRs and their respective 2DTFs of an animation of the IVW in the context of the climate dataset. While the initial rendering (left) presents a region of many possible isosurface realizations based on a wide IVW, the other renderings show later animation states, where the less probable areas are continuously faded out. Additionally, the thickness of the region at a position is an indicator of the uncertainty in this area. This can especially be seen on the left vertical part of the renderings.

the change of thickness on the left side of the image, where in the beginning the vertical area is far wider than in the last rendering. In addition to this, the colors used in the visualization show the local amount of uncertainty. The blue and teal areas in the last rendering are the ones where it is the most uncertain that they actually have a value of approximately 0 °C.

Pöthkow and Hege (Pöthkow and Hege, 2011) created a static visualization of the isosurface variability for the same data and isovalue. Their visualization is comparable to the initial rendering of Figure 8. The advantage of an animation of the isosurface variability, is that one is able to see the change between the more and less certain surface realizations.

5 LIMITATIONS

The presented approach exploits the high sensitivity of the visual perception to oscillating visual features which is captured in the *temporal contrast sensitivity function* (Ramamurthy and Lakshminarayanan, 2015). While humans are capable of identifying that two animations differ in speed, it is not possible to quantify the frequency of an animation. Thus, animations are not a suitable visual channel to support comparison tasks (Brown, 2004). Using animations to highlight time-dependent datasets is impractical, as it is impossible to distinguish between changes caused by unsteadiness or by the animation itself.

The observation that animation of the DVR can cause visual fatigue (Lundström et al., 2007) limits the time the new method can be used effectively. This, however, does not impede a central goal of the new approach, i.e. providing a quick overview with a pre-attentive highlighting of regions with uncertainty.

Simple DVR performance optimization techniques like progressively resolution during user inactivity (Meyer-Spradow et al., 2009) can not be combined with *pulsating uncertainties*. The animation continually alters the content that needs to be rendered. A solution could be to extend such techniques by pre-computing high resolution renderings of animation frames as soon as the user interactions stops.

6 CONCLUSION AND FUTURE WORK

In this article, we presented animated two-dimensional transfer function widgets as an uncertainty highlighting mechanism for scalar fields with uncertainty. In addition to the highlighting, the animation serves as a means to automatically explore the data and its uncertainty while users can focus on the spatial exploration by manually interacting (e.g. rotating) with the scene. The constant speed of the animated TF additionally allows judging the rate of change of uncertainty between different areas in the rendered scene. One of the introduced TF widgets, the isosurface variability widget, enables users to inspect the variability of isosurfaces. Until now this has been solved by the literature as specializations of contouring and volume rendering algorithms for data with uncertainty. As the method is not limited to data from a certain domain, we were able to demonstrate its expressiveness on data from diverse domains.

Animated 2DTFs open many avenues for future work in uncertainty visualization. Instead of the standard deviation the level-crossing probability (LCP) (Pöthkow and Hege, 2011) could be used for the *y*-axis of the 2DTF. The advantage of the LCP is its capability to deal with non-parametric models of uncertainty. The interpretation of the animation and visualization would be a challenge for this research. We present only a limited amount of widgets for animation. Further widget designs and animation types (scale, rotate, translate) could be used to explore the complex data sets with uncertainty in other meaningful ways. It is obvious that animation works well for highlighting, nevertheless analyzing which animation speed is most effective could be interesting.

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