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Integrated Spatial Uncertainty Visualization using Off-screen Aggregation

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Abstract

Visualization of spatial data uncertainties is crucial to the data understanding and exploration process. Scientific measurements, numerical simulations, and user generated content are error prone sources that gravely influence data reliability. When exploring large spatial datasets, we face two main challenges: data and uncertainty are two different sets which need to be integrated into one visualization, and we often lose the contextual overview when zooming or filtering to see details. In this paper, we present an extrinsic uncertainty visualization as well as an off-screen technique which integrates the uncertainty representation and enables the user to perceive data context and topology in the analysis process. We show the applicability and usefulness of our approach in a use case.

1. Introduction

Spatial uncertainty visualization aims at presenting data and its inherent uncertainty simultaneously. This is important for informed decision making where the quality of the underlying data plays a crucial role. The data exploration implies two challenges: Firstly, data values and corresponding uncertainties need to be integrated in a meaningful visualization and secondly, analysis tasks often require to focus certain regions. For example, when inspecting temperature distributions and their quantified uncertainty (see Figure 2), analysts will need to examine locations in detail but also draw conclusions regarding their comparison to the surrounding. As a result, one has to compromise between *Overview and Detail*.

Established uncertainty visualizations present data and uncertainty intrinsic and integrated into one viewport (coincide) [KMS14]. In intrinsic representations, the color that represents the data value is in most cases modified to indicate uncertainty. As a result, uncertainty cannot be easily quantified and data values are not preserved. We therefore target an extrinsic visualization. Furthermore, to support navigation during exploration, we aim at integrating the overview into the visualization, because using a second viewport forces the user to split his attention resulting in cognitive load [Gru01]. Integrated techniques, such as Focus-plus-Context, are mostly image-driven and distort the space which impairs the ability to make relative spatial judgments [CKB09]. In contrast, off-screen techniques support navigation through visual cues located at the display border but lack in presenting the data topology. Off-screen techniques maximize the focus but require adaption for extrinsic uncertainty visualization and tasks that require knowledge about topology.

We therefore propose to surround the viewport by a border which incorporates the extrinsic representation of uncertainty in a topology-preserving way. We design an extrinsic glyph which allows the user to discretely perceive data and uncertainty values using the occlusion metaphor: occluded data values appear less certain than non-occluded values.

We contribute an extrinsic uncertainty visualization using the Figure-Ground organization. We further contribute an off-screen visualization technique, which incorporates the extrinsic uncertainty visualization and supports the analysis. Further, we showcase the usefulness in a use case.

2. Related Work

2.1. Uncertainty Visualization

MacEachren et al. [MBP98] asserted that importance should not only be given to the visual syntactic with which uncertainty measures are matched with visual variables, but also to the way data and uncertainties are linked and represented. As such, Kinkeldey et al. [KMS14] mention three prominent dichotomous categories for uncertainty visualization, considering work of Howard and MacEachren [HM96] and MacEachren [Mac92], among others: intrinsic/extrinsic (w.r.t. situating data and uncertainty), coincident/adjacent (w.r.t. view organization), and static/dynamic (w.r.t. to the interactive nature of the display). Most existing uncertainty visualizations focused on intrinsic, coincident, and static techniques, while extrinsic and adjacent techniques are seldom being used [KMS14]. Dynamic techniques, which involve user interaction in most cases, are sparse. It is shown through studies such as by Senaratne et al. [SGPS12], that such techniques require advance experience in spatial uncertainty analysis.

Glyphs have become most popular among extrinsic visualizations due to their multivariate nature, and are utilized to represent variables through various parameters such as location, shape, size, color, orientation, aspect ratio, or curvature [BKC*13]. Works by Pang [Pan01] and Cliburn et al. [CFMS02] have demonstrated the use of glyphs for uncertainty visualization in geo-spatial data under various settings.

2.2. Focus-plus-Context and Off-screen Visualization

Context-preservation is crucial for efficient analysis and navigation in large data spaces. Context includes knowledge about data characteristics and topology. Focus-plus-Context and Off-screen techniques aim at integrating both, focus area and context, into one representation.

The pioneering approach by Apperley et al. [ATS82] distorted the surrounding and provided maximum focus at the same time. Furnas [Fur86] further introduced the degree-of-interest (DOI) function as the general basis for Focus-plus-Context systems (like e.g. [CM01]). A comprehensive review of additional Focus-plus-Context techniques was carried out by Cockburn et al. [CKB09]. Despite the advantage of seamlessly integrated detail and overview, some weaknesses remain: due to distortion, relative spatial judgments remain challenging [CKB09] and the focus area is restricted by means of possible zooming levels [MCH*09].

Unlike mainly image-based Focus-plus-Context approaches, Off-screen visualization aims at providing a data-driven overview of objects located outside the viewport. Also, well-known techniques for graphs exist, but which we will not review as it is beyond the scope of this paper. Off-screen makes use of visual cues located at the display border, which indicate the relative distance and direction to points-of-interests (POIs). Apart from arrows, Zellweger et al. [ZMG*03] propose CityLights as family of techniques: Halos and City Light cues. While City Light cues only visualize existence and orientation of POIs, Halos [BR03] show distance and location by intersecting the display with an arc. However, despite improvements [GBGI08, GACP11], distance perception is not optimal for large amounts of data in dynamic environments. Games and Joshi further proposed to use visual cues for augmented analysis of bar charts and scatterplots [GJ13].

In spite of several studies and improvements, data topology and multivariate data are yet barely considered. In this paper, we adapt the idea of City Light cues and EdgeRadar [GI07], but add information about data topology, and encode off-screen data and its uncertainty in an extrinsic glyph. Furthermore, we apply grid-based aggregation to off-screen located data entries, whose relative distance in the border region – after mapping – leads to overlap. We showcase how such glyphs are utilized to characterize the varying uncertainty of temperature measurements over Germany in a coincident representation over the underlying data using off-screen aggregation.

3. Off-screen Uncertainty Visualization

In the following, we describe the design choices taken for the visualization of uncertainty and off-screen data.

3.1. Extrinsic Uncertainty Visualization

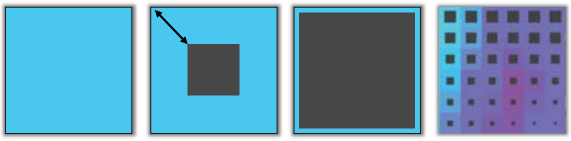


Figure 1: *Occlusion metaphor: the less occluded a data value is, the less uncertain it is. From left to right: (1) Minimal uncertainty. The grid cell is not occluded. (2) Partial uncertainty is presented as distance from the cell's to the occluding rectangle's boundary. (3) Maximum uncertainty leaves a whit of the data value. (4) Visualization in a grid-based environment.*

For the integrated visualization of data and uncertainty, we encode two visual variables in addition to position [Mac86]: color represents the data value and size of the occluding rectangle represents its uncertainty value. We use the occlusion metaphor to encode uncertainty and add a black rectangle on top of the grid cell whose size defines the amount of uncertainty. The less occluded the data representation is, the less uncertain it is (see Figure 1). The choice of the rectangle size to indicate uncertainty results from the grid-based approach. However, uncertainty is not represented precisely this way, but provides an effective overview on the data; the precise perception of uncertainty is not a strict requirement of this application. In our application scenario, we use the cold color map from cyan to magenta to visualize the varying cold to very cold temperature values. These colors show a high saturation and can be perceived and identified, even if they are partly occluded by a dark rectangle since the contrast is very high [Sch56]. This approach is adopted from Oelke et al. [OHR*09], who used a similar glyph representation for visual opinion analysis. Furthermore, Stoffel et al. [SJM12] visualized electoral results and used the distance from outer to inner shape to visualize first and second placed parties.

We additively derive our design decision to use the occlusion metaphor from Edgar Rubin – data and uncertainty are grouped according to the *Figure-Ground organization* [Rub15]. Depending on what the user focuses, she either perceives the actual data values (background) or the uncertainty values (foreground).

As depicted in Figure 2, we use the glyph in two variations. Either the glyph is integrated in a grid that visualizes off-screen content (left and right images) or simply overlays the map (center image), or the glyph is used to provide discrete information on the map. The left and right images show the glyph as discrete representation and the application to the German temperature measuring stations. A more detailed description follows in a use case in Section 4.

3.2. Visualization of Off-screen data

When using visualizations to explore data, we usually follow the Visual Information-Seeking Matra: *"Overview first, zoom and filter, then details-on-demand"* [Shn96]. In uncertainty visualization, topology-awareness and analysis tasks such as comparison or identification of data values, among others, play a crucial role. In order to provide a maximum focus region as well as topology-awareness of surrounding data and its uncertainty, we augment the viewport with a dedicated border region which incorporates the glyph described in 3.1. The idea of providing a rectangular shaped maximum focus is inspired by bifocal displays [ATS82] and possible misinterpretations caused by radial viewports [ZCR02]. The usage of such a dedicated border instead of visual proxies implies the preservation of data topology as well as a solution for the so called *Desert Fog* problem defined by Jul and Furnas [JF98]: Empty regions are simply identifiable and hence, the user is able to efficiently navigate to regions of interest. This way, we are able to save zoom and pan iterations and augment the Visual Information-Seeking Mantra: Overview first, zoom and filter, then overview and details-on-demand.

The dimensions of the dedicated border region depend on various factors: the zooming level, the position of the focal area in the data space, the data distribution, and the analysis task. There is no unique definition of dimensions since there exist many different combinations of factors influencing this design decision. We therefore propose the concept of an adaptive off-screen border:

$$B_{size} = B_{maxSize} - \left(\alpha \cdot \frac{(B_{maxSize})^2}{d(P_{vc}, P_{oMax})} \right) \qquad (1)$$

A constraint for the calculation of the adaptive border width B_{size} is, that the zooming level is at least that high, so that the focal area is covered by the data space. Otherwise, off-screen data does not exist and the border region is void. In each interaction step – zooming or panning – B_{size} is adapted. Therefore, we first derive the relative scale from the relation between maximal possible border size $B_{maxSize}$ and the distance between viewport center P_{vc} and maximal outer bounds of the data space P_{oMax}. The value $B_{maxSize}$ is limited to half of the the display dimensions (use half of the display height if the display is widescreen, width otherwise). Visual Analytics argues that the user plays a crucial role in the exploration process [KMS*08]. We therefore introduce the parameter α. The user can select the α value between $[0,1]$ and thus determine the relative maximal size of the border region with direct impact on $B_{maxSize}$. Depending on the position of the viewport and the zooming level, the border region gets more space assigned the higher the zooming level is and the more data needs to be represented within the border region.

In many cases, uncertainty data is determined and presented as a grid, which suggests the choice of a grid-based visualization. This choice entails different advantages: The visualization is overlap-free and also generalizable, because any glyph representation can be integrated into grid cells.

When squeezing information into the border region, there might not be enough space to visualize each data value and its uncertainty, derived from the initial grid, separately. Hence, we first map each entry to the border region and then overlay mapped entries with our grid-based glyph. Multiple values sharing one grid cell are averaged so that the data value and the uncertainty value of the glyph are aggregated respectively. In order to map off-screen located data to the border region, we use point-to-point navigation and draw a virtual line between viewport center and off-screen data object. The following formula describes the new relative distance from the viewport boundary to the mapped data point within the dedicated border region:

$$d(P_{bMin}, P_{new}) = \frac{d(P_{vc}, P_o)}{d(P_{vc}, P_{oMax})} \cdot d(P_{bMin}, P_{bMax}) \qquad (2)$$

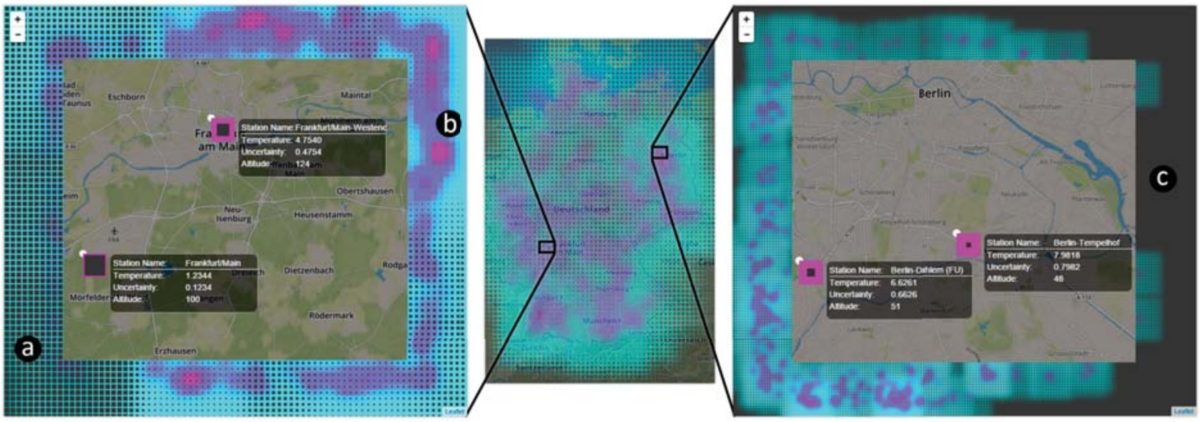
P_{oMax} is the off-screen point located the farthermost from the current viewport. Since the distance mapping on the border region is supposed to be global, we first derive the linear distance scale from the distance between viewport center P_{vc} and the off-screen located data object P_o relative to P_{oMax}. The virtually drawn connection between P_{vc} and P_o intersects the border in the points P_{bMin} and P_{bMax}. The distance between P_{bMin} and the new location P_{new} can then be defined by multiplying the size of the border $d(P_{bMin}, P_{bMax})$ with the distance scale.

Figure 2 shows the final result. The glyph can be either used as map overlay or within the off-screen environment. By using the Figure-Ground organization, one can easily distinguish between data values and uncertainty distribution, which enables common analysis tasks like comparison, localization, and identification.

4. Use Case

In this use case, we make use of a scalar dataset of temperature measurements collected from weather stations throughout Germany. The data originates from the German Weather Service (Deutscher Wetterdienst) and serves as the basis for the creation of a grid-based artificial dataset, for which we used standard deviation to derive the uncertainty values.

Our use case involves climate researchers working for an environmental agency who are responsible for the planning and implementation of a national scientific measurement infrastructure for the observation of climate changes. For their task, it is important to view the temperature distribution of the



Station Name: Frankfurt/Main-Westend
Temperature: 4.7540
Uncertainty: 0.4754
Altitude: 124

Station Name: Frankfurt/Main
Temperature: 1.2344
Uncertainty: 0.1234
Altitude: 100

Station Name: Berlin-Dahlem (FU)
Temperature: 6.6261
Uncertainty: 0.6626
Altitude: 51

Station Name: Berlin-Tempelhof
Temperature: 7.9818
Uncertainty: 0.7982
Altitude: 48

Figure 2: *The uncertainty visualization applied as topology-preserving off-screen technique. The center image shows the temperature distribution in Germany. The extrinsic uncertainty visualization allows an easy identification of (a) uncertain regions, (b) certain regions, and (c) regions without any values. Left and right image show different levels of detail within the border.*

entire country but they also want to find out in which regions the sensor network needs improvement for better coverage. Reviewing the uncertainty values for a region is the solution for this task, as the uncertainty indicates poor quality of measurements in the area. Thus, we quantify the uncertainty and apply the uncertainty visualization as shown in 3.1.

Inspecting regions on a more fine-granular level makes it necessary for the analyst to zoom the viewport. He then can spot additional data features such as station altitude, average precipitation or sunshine, among others. The availability of many different features is typical for multivariate datasets. To prevent overplotting and occlusion issues when displaying all attributes, we provide a details on demand capability as depicted in Figure 2.

Thanks to the topology-preserving off-screen visualization, the analyst is now able to compare temperature and uncertainty values of off-screen located regions of arbitrary detail with the rest of the dataset conveniently. As the uncertainty value is represented in the border region for the whole dataset, the analyst can also easily observe the uncertainty development in every direction seen from the currently chosen viewport. If one of the off-screen regions seems interesting, for example due to high uncertainty, the analyst furthermore is able to directly navigate there by one click, thus saving time-consuming panning and zooming operations.

5. Concluding Remarks and Perspectives

We have presented an extrinsic uncertainty visualization and a data-driven off-screen visualization that preserves context and topology. We further have demonstrated the usefulness of our approach within a use case for climate research where uncertainty visualization is of key importance for informed decision making. Data and its inherent uncertainty are integrated into a coincident representation. Out of the well-established uncertainty visualization techniques in the literature, we have chosen the extrinsic technique to depict the uncertainties in the data by the use of an occlusion glyph. Accordingly, the tool facilitates a viewport for detailed view of data and uncertainty, and a topology preserving border region for displaying the overview of data and uncertainty.

Compared to distortion-based approaches like Fish-Eye lenses, our approach allows more zoom stages and preserves the topology at the same time. In comparison to other Overview-and-Detail approaches, only one viewport is necessary to display overview and details. Lastly, our approach addresses the Desert Fog problem. Due to the used border, the user is aware of the whole data space and perceives areas that do not contain any data. As a result, zooming and panning interactions are saved. By integrating off-screen visualization with state of the art extrinsic coincident uncertainty visualization techniques, we have solved the following problems: (1) *Saccading* effects seen typically in adjacent techniques (that causes the user to lose focus) and (2) *cognitive load* typically seen in coincident techniques (that require higher mental efforts to comprehend data and uncertainty independently).

In future work, we will evaluate our approach, particularly with respect to the level of detail of the glyph and the border size having regard to user settings. Although the aim is to have the highest level of detail (small glyphs and relative big border), this may vary depending on which level of detail we can quantify the uncertainties in the data. Furthermore, we will incorporate other topological features to the overview border (e.g. elevation to highlight the underlying surface) and integrate our approach into a Visual Analytics system allowing the user to interactively change model parameters and explore the data.

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