MANAGING UNCERTAINTY IN VISUALIZATION AND ANALYSIS OF MEDICAL DATA

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ABSTRACT

The principal goal of visualization is to create a visual representation of complex information and large datasets in order to gain insight and understanding. Our current research focuses on methods for handling uncertainty stemming from data acquisition and algorithmic sources. Most visualization methods, especially those applied to 3D data, implicitly use some form of classification or segmentation to eliminate unimportant regions and illuminate those of interest. The process of classification is inherently uncertain; in many cases the source data contains error and noise, data transformations such as filtering can further introduce and magnify the uncertainty. More advanced classification methods rely on some sort of model or statistical method to determine what is and is not a feature of interest. While these classification methods can model uncertainty or fuzzy probabilistic memberships, they typically only provide discrete, maximum *a-posteriori* memberships. It is vital that visualization methods provide the user access to uncertainty in classification or image generation if the results of the visualization are to be trusted.

Index Terms**—** Scientific Visualization, Uncertainty, Sensitivity, Data Processing, Computer Graphics

1. INTRODUCTION

The Nobel laureate Richard Feynman once said, "What is not surrounded by uncertainty cannot be the truth." In science, any measurement or calculation is accompanied by a measure of uncertainty, or expected variability in the quantity. Knowledge of uncertainty can be as valuable and interesting as the measurement itself. It conveys the degree to which a measure can be trusted and is a key indicator of the quality of the process or calculation. Uncertainty may not always describe error; in many situations, the phenomena or feature being observed takes on a range of values and is best expressed as a distribution rather than a single discrete value. While visualization methods are widely recognized as an essential component of modern scientific data analysis, image generation and interaction techniques rarely account for uncertainty in the raw data and filtering, much less provide a visual indication of its presence.

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2. UNCERTAINTY

The National Institute of Standards and Technology, NIST, and the National Center for Geographic Information and Analysis, NCGIA, define *standard measurement uncertainty* as the standard deviation of a measured value [1, 2], for instance $3.5 \pm .70m$. The NIST definition of *expanded measurement uncertainty* is an interval that captures the true value of a measurement with some level of confidence, for example $3.5 \pm 1.2m$ with 99% confidence. Our work deals primarily with classification results. In this case, we are interested in a *stochastic uncertainty*, which may be regarded as the complement of a class posterior probability, *i.e.* $1 - P(\omega|x)$ where $P(\omega|x)$ describes the probability of class ω given feature vector x. It is also valuable to consider uncertainty as it relates to the decision making process. A derived quantity known as risk can provide a quantitative measure of the cost associated with a particular decision. Other derived measures based on risk include physical units such as distance a decision boundary will move per unit change in prior probability or risk.

Figure 1 illustrates the value of uncertainty information in visual data analysis using a synthetic 2D example. Figure 1-A shows the ground truth synthetic model, which has five different material classes. In this example, we simulate raw data (Figure 1-B) by assigning a unique intensity value to each of the materials, rasterizing them into a 256^2 image, blurring the result (to simulate a band-limited image), and finally adding three percent normally distributed noise (typical of acquired data). Figure 1-C shows four relevant isovalue thresholds (taken at intervals between the class means) as subimages. This is analogous to isosurfacing in 3D. Notice that few of the thresholds manage to capture distinct materials when compared to the ground truth image. Figures 1-D through H use classified data to perform color mapping. The posterior class conditional probabilities were estimated using the known parameters; mean data value, noise distribution, and a neighborhood size proportional to the blur kernel. In Figure 1-D, colors were weighted by the class probabilities and blended together. This color mapping is a fuzzy syntactic method. Figure 1-E shows the image color mapped based on the class with the maximum probability (0-1 risk decision), as is commonly done in classification algorithms. This kind of data is also called "tagged data". There is no indication

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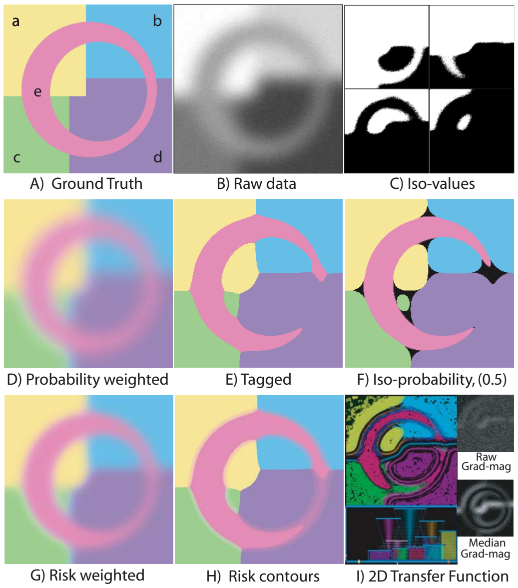

Fig. 1. A 2D example of probabilistic boundary behavior. **A**) The synthetic dataset, consisting of five materials. **B**) The raw dataset constructed from a blurred monochrome version of the synthetic dataset with noise added. **C**) The four most relevant iso-value thresholds of the raw data as subimages. **D**) An image colored based on the class conditional probabilities of the classified raw data. **E**) A "max-probability" tagged image. **F**) The data set color mapped based on a probability threshold of 0.5. **G**) An image colored based the probability ratios (risk curves). **H**) An image showing several risk contours for material "e". **I**) Data color-mapped using a carefully hand tuned 2D transfer function, based on raw data value and the gradient magnitude of the median filtered raw data.

of uncertainty in this image. Figure 1-F shows a color mapping based on class probabilities greater than a threshold of 0.5 for all classes; all data values containing a probability less than 0.5 are shown as black. This is equivalent to isosurfacing the class probabilities. Figure 1-G shows the image with colors weighted based on risk. Notice that the boundaries are crisper than in the probability weighted example and that the variation in thickness for the loop (material e) is easier to see. This example combines syntactic and semantic approaches, since the color mapping is fuzzy, but more directly related to alternative realizations of the structure. Figure 1-H shows a color mapping based on the 0-1 risk decision, with the addition of two risk-based decision contours for material e. This is an example of a semantic method; the contours clearly indicate important variation in the classified material. Finally, Figure 1-I shows a color mapping made using a carefully designed 2D transfer function, based on data value and gradient magnitude. Because gradient estimation is highly sensitive to noise, the 2D transfer function performed quite poorly with the raw data (top-right subfigure), even though the gradient was estimated using the derivative of a cubic b-spline kernel, which implicitly blurs the data. To accommodate for the noise, the data required further pre-processing using a median filter (introducing additional uncertainty) with a width of five pixels before gradient computation (Figure 1-I, bottom-right subfigure).

3. DIRECTIONS

Our work focuses on three primary aspects of uncertainty in visualization:

- Establishing new methods for the rendering and display of features in volume data that expose uncertainty and variation. Our work emphasizes interactive characteristics of the visualization that provide concrete examples of features and a structured exploration of variant uncertainty realizations.
- Developing and adapting computational classification methods that preserve uncertainty and propagate this uncertainty through to the final visualization stage. We are developing a framework for quantifying uncertainty at each stage of the visualization pipeline and preserving it for use in rendering and interaction.
- Creating ground-truth phantom models for validation. We leverage classification results to develop synthetic models that capture the expected variation of real structures and simulate the errors introduced through data acquisition and discretization.

Our goal is the development of visual tools that move the field of visualization forward as a precise science of discovery. Defining and understanding the role of visualization in decision making is a key task that we are addressing. Exposing and quantifying uncertainty is essential in decision making. Knowledge of alternatives and the potential for error allows one to make a more informed decision and manage the cost associated with an incorrect judgment.

The successful integration of uncertainty and visualization will capture the semantic meaning of uncertainty as it relates to structures that appear in the rendered image. A semantic visualization of structures in the presence of uncertainty exposes the variation in the structure's shape resulting as a consequence of uncertainty. When there are many possible realizations of the feature shape or structure these variations should be available to the user as alternatives for use in the decision making process. Contrast this with a syntactic view of uncertainty visualization. In this case, the visualization method portrays uncertainty as fuzzy, noisy, or distorted regions. While this can alert the user to the presence of uncertainty, these methods do not depict a specific realization of a structure and possible variations. Our aim is to develop techniques that clearly present structural variations due to uncertainty. Figure 2 illustrates several concrete realizations of the anatomically ambiguous boundary between white and gray matter in the brain. Exploration of these variations is a central component of our interactive visualization system.

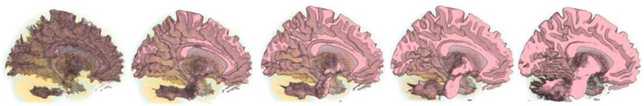

Fig. 2. Variation in classification of white matter in MRI data.

3.1. Display

The first goal of this research is to develop new methods for visually communicating uncertainty in visualization applications. These methods should not only indicate locations of high uncertainty, but also the semantic meaning of uncertainty; that a range of decisions or class assignments are possible. Figure 2 illustrates how a visualization of white matter in a MRI scan can involve many possible realizations. The method utilizes a probabilistic classification method that preserves uncertainty in the boundary between white matter and gray matter [3]. While a component of this uncertainty can be tied to the limits of the acquisition method, *i.e.* noise and band-limiting, parts of this boundary are inherently fuzzy. In reality, the transition from white to gray matter in the cerebral cortex is gradual; there is no distinct anatomic boundary between white and gray matter. Any classification that produces a distinct boundary in this region of the brain will be arbitrary. Figure 3 illustrates the difference between a syntactic presentation of uncertain information versus a semantic presentation. Figure 3A shows the white matter where the fuzziness of the rendering indicated the degree of uncertainty. This is a purely syntactic approach, uncertainty is associated with fuzziness so the rendering maps opacity based on uncertainty, producing the fuzzy appearance. Figure 3B presents classification uncertainty using a color gradient, which indicates the degree to which the classification would change if the prior probability of white matter were changed. We can say that this method has both the properties of a syntactic approach (color is used to indicate uncertainty) and a semantic approach (the quantity being color mapped is based on the degree to which there are multiple realizations of the surface). Figure 3C shows three confidence intervals simultaneously as red, white, and blue surfaces. This is an example of a purely semantic approach, showing multiple realizations of the white matter class.

Our approach for visualizing classified data advocates decoupling the processes of classification (identifying objects in the data) from the transfer function (specification of color and opacity). To allow interactive exploration, we defer decision making (specification of a specific realization of the object) until a sample is rendered. This requires the fuzzy class probabilities to be included with the data used for rendering. The

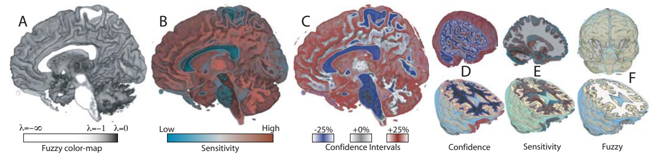

Fig. 3. Visualization of white matter with uncertainty in a static image. A) a fuzzy rendering (syntactic), B) a color map based on change in surface position per unit change in risk (syntactic and semantic), C) confidence intervals as nested surfaces (semantic). D, E, and F show additional views and structures for each of the methods.

advantage of using the fuzzy probabilities is that they interpolate, unlike discrete class assignments, and allow the optical property assignment, or transfer function design to be greatly simplified. The difficulty is identifying accurate fuzzy probabilities, especially when the desired classifier does not explicitly compute them.

3.2. Capturing Uncertainty

We are currently working with three classification methods that poses important characteristics related to uncertainty visualization; those which explicitly compute partial class probabilities, those that do not, and those that can be adapted to produce them.

- **Boundary Model Expectation Maximization** This classifier relies on a model of structure and data acquisition, which allows one to create a feature space from derivative measures [4, 5]. This feature space is commonly used for *ad hoc* transfer functions in traditional volume rendering [6]. The feature space, based on data value and derivatives, can be used with an Expectation Maximization classifier, which identifies the ideal parameters for a mathematical model of structure. Such a classifier computes partial class probabilities, which can be used for risk analysis and decision making in the rendering stage of the visualization pipeline.

- **Level Set Classification** Level sets have been used extensively for segmentation of image data [7, 8, 9]. This segmentation algorithm can be thought of as a classifier that uses spatial position in addition to data as elements of the feature space. This classifier does not compute explicit partial class probabilities and will require sensitivity analysis methods to utilize measurement error and compute class uncertainties.

- **Random Walker Classification** Like level set methods, random walker classification/segmentation [10] uses a PDE to compute the results. Current random walker classifiers do not explicitly compute partial class probabilities. However, they can be adapted to produce them by modifying the algorithm without resorting to external methods like sensitivity analysis.

3.3. Validation and Phantom Models

Our primary goal in constructing ground truth phantom models is to have control of the data generation process. Such control allows us to isolate and analyze sources of uncertainty that are typically outside our control, for instance data acquisition error and noise. Furthermore, phantom models and simulated acquisition will allow us to directly compare the synthetic reality with our uncertainty measurements. Our approach to phantom model development is based on the successful BrainWeb Phantom project [11]. This synthetic model allows one to generate simulated MRI scans of a human brain with a specified resolution, imaging technique (PD, T1, T2), noise properties, and field inhomogeneities. The generation of synthetic data relies on an underlying model of the anatomic structures, which is derived from multiple hand segmentations. The anatomic structures preserve the natural fuzzy qualities, such as the boundary between white and gray matter in the cerebral cortex. The method then simulates the physical process of data acquisition to generate realistic raw data. This project has been a valuable resource for many conducting classification and segmentation research on this class of data. While this class of data is an important application area for the proposed methods, it only represents a fraction of the data types that benefit from volume visualization.

Our validation work focuses on the following:

- Identify and classify/segment representative models from the areas of Non Destructive Testing CT, human and mammal CT, human PET, human brain FMRI, and Numerical Weather Simulation. Together, they represent the majority of data types for which our collaborators and users require visualization. We currently have multiple exemplar sample data sets in each class.
- Develop a reasonable simulation of the image acquisition process for each of these data classes. We are developing a single framework for the simulation process which introduces control of noise, geometric distortion, and structure variation.
- Develop a system for automated analysis of the proposed classification methods using a wide range of noise and distortion characteristics. Our aim here is to validate the proposed classification methods to insure that uncertainty estimates are always conservative, *i.e.* the methods do not underestimate the uncertainty.

4. REFERENCES

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