Uncertainty Visualization – Why Might it Fail?

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Abstract
There is a gulf between the rhetoric in visualization about the importance of uncertainty, and the practice of visualization in which uncertainty is rarely seen other than as a laboratory exercise. We reflect on why something viewed as fundamental in science and engineering is rarely if ever adopted in visualization practice. Our analysis is informed both by research progress and by our own experience in an ongoing industrial case study on modelling and mapping underground assets, where it would appear that uncertainty plays a major role. In this case study, we try to identify promoting and limiting factors. We conclude that the value of uncertainty visualization is severely limited by the quality and scope of uncertainty data, by the limited confidence in the data itself, and by the perceptual and cognitive confusion that the depiction of this data can generate. We hope to broaden the discussion on the utility of uncertainty in visualization from the purely technical and perceptual issues to social and organizational factors.

Keywords
Uncertainty visualization, maps, utility data, service plans.

ACM Classification Keywords
H5.m. Information interfaces and presentation.

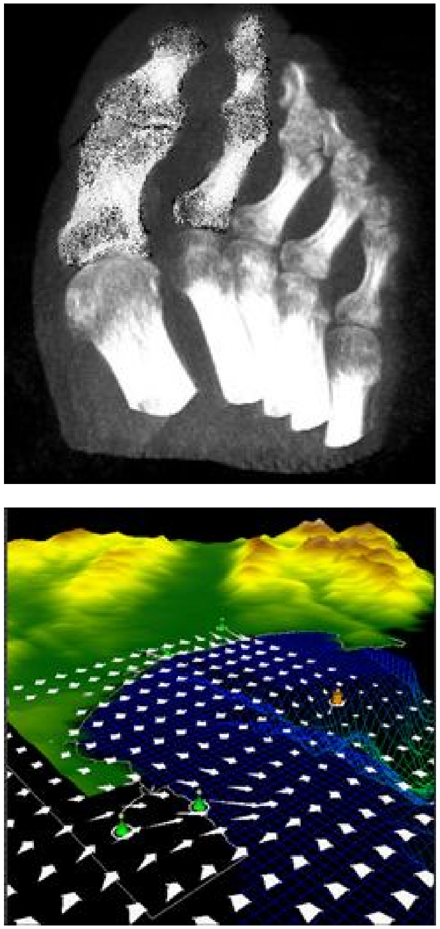

Figure 1 [Top] An image showing bones of a human foot rendered illustratively to indicate areas of low quality information [8]. [Bottom] Vector glyphs to visualize uncertain winds and ocean currents [7].

Uncertainty visualization is concerned with presenting data alongside auxiliary information such as accuracy, error or other factors of provenance that influence interpretation and judgement. There are various fields where uncertainty information is vital to making accurate interpretations of data. In the physical sciences and engineering, for example, it is rare to publish a graph that did not involve some indication of accuracy, either explicitly or via annotation. Yet in visualization, such indicators are not the norm.

We give a critical analysis of uncertainty visualization techniques and applications. We first provide a brief background on research in uncertainty visualization using a three-stage conceptual pipeline covering provision, depiction and usage. We then apply our three-stage analysis to an industrial case study on modelling and mapping underground assets. Finally, we reflect on our experience so far in a commercial project (VISTA) and try to identify promoting and limiting factors.

Understanding Uncertainty

There has been a number of surveys on uncertainty visualization, each concentrating on a specific aspect such as depiction [4], a particular domain such as Geographical Information Systems [5], or a specific type of uncertainty such as risk [1].

Various Definitions and Taxonomies

Numerous definitions of uncertainty can be found in the literature reflecting the range of concerns that come under the general term. Often the relationship between *accuracy* and *uncertainty* is debated. In cartography, uncertainty and data quality have a close link and the two terms are sometimes used synonymously. Despite the different notions of uncertainty and the varied usage of this term, there is general agreement that uncertainty is understood as a composition of multiple concepts. Uncertainty visualization is, however, very application-specific, and which sources of uncertainty are chosen and how data is represented varies widely.

Multiple Stages and Pipelines

We describe uncertainty visualization as a three-stage process (Figure 2) requiring different skills and types of knowledge at each stage: domain knowledge at the data provision stage to determine the relevant sources of uncertainty and how they should be modelled; visualization skills to decide best methods to depict uncertainty; and the ability to interpret presented information and use it within the context of a task.

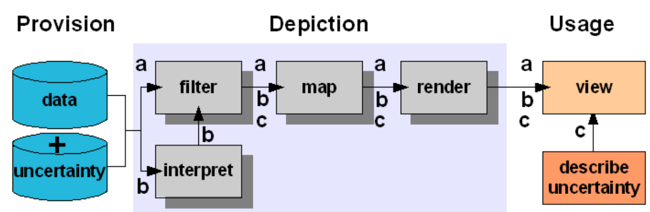

Figure 2 Three routes for uncertainty in visualization: [a] explicit modelling with the data, [b] implicit modelling where data is first interpreted in light of the available uncertainty information [c] informal interpretation at the user end.

Three Key Challenges

First, one might ask whether metadata about uncertainty is inherently any different from other data that are processed in the visualization. Uncertainty can be provided as secondary data not requiring immediate user attention or embedded with the primary data itself and available within the standard pipeline. *Second*,

Figure 3 A single domain service plan showing gas pipes in red.

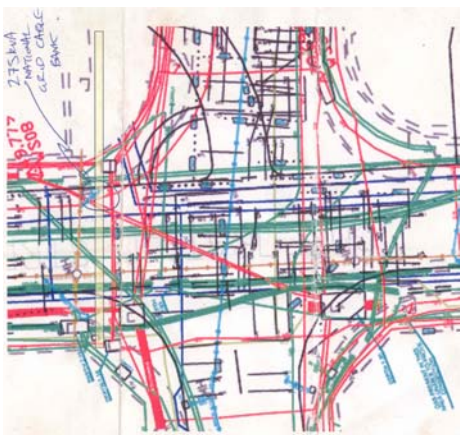

Figure 4 An on-site plan showing multiple utility domains.

there is the issue of finding a representation that is compatible with the primary data, the tasks served by the visualization, and the organizational importance assigned to the uncertainty. Options include use of high salience symbology (e.g. "danger symbols"); incorporation within the primary data display (e.g. error bars); or utilising low-key secondary displays. The difficulty is to blend the graphics without overshadowing critical data. *Third*, there is the challenge of assessing how uncertainty information is used, for instance to support decision making.

Decomposing the Pipeline – The Literature

Sources of uncertainty may reside at the acquisition stage due to errors in measurements; when filtering because of incomplete knowledge; during modelling as a result of inappropriate visual mappings; when rendering due to approximations in illumination calculations or at the comprehension stage caused by human bias, subjectivity and incomplete knowledge.

Provision – how do we model?

Uncertainty information can be collected from the real world or simulated using statistical modelling. It can be derived automatically or interactively attached as metadata with quantitative or qualitative values. Categories of confidence in data can be expressed by assigning values to pre-defined uncertainty classes, ranges of values or sets of possible values, and can also be described quantitatively by scalar values like probability and error percentages [4].

Depiction - how do we show?

Although uncertainty information may be communicated textually or numerically, visual depiction is usually preferred especially when this uncertainty is related to risk [1]. When information about uncertainty is available, it is incorporated in the display either by altering the appearance of the underlying data (e.g. Figure 1-top), or by creating new visualization primitives separately from the underlying data (e.g. Figure 1-bottom). Although various examples of depiction techniques may be found in the literature, there is a mismatch between efforts to conceptualize, represent and use uncertainty information.

Usage – how do we know?

Does it enhance the task? The fitness of uncertainty representation for a given task have been investigated by a number of researchers; e.g. [3] set out to test the effectiveness of visual mappings by examining user performance when interacting with different depiction methods. They found that subjects performed better using a combined view (either as static or animation) than separate or toggled views.

How useful is it? If we adapt the visualization to depict uncertainty, will users incorporate this information into decision making, or do they rely on heuristics in making judgements? Other related questions are concerned with whether different users incorporate uncertainty information in the same way, or their level of expertise, prior knowledge or other factors play a role in how this information is incorporated in decision making.

Does it matter? Does the inclusion of uncertainty information in representation actually improve decision making? Such evaluations study the degree of influence on user confidence and whether this degree of influence depends on the nature of the decision task or other factors. For example, this influence may depend on how uncertainty is expressed [2] (e.g. texture or value).

Figure 5 Depicting uncertainty using blur: different levels of positional accuracy for water pipes are denoted by different levels of blur.

Figure 6 Depicting uncertainty using colour bands: grey denotes sewer pipes and magenta denotes the Ordnance Survey (OS) backdrop. Colour bands denote locational confidence: green for accurate, yellow for probable and red for uncertain.

The evaluation of uncertainty visualization is a complex task and requires consideration of multiple parameters such as the visual domain (e.g. map or plot), methods of depiction (e.g. intrinsic or extrinsic), user (e.g. novice or expert), task (e.g. detect or assess) and potential impact. Evidence suggests that the way uncertainty is expressed can influence the effectiveness, the usefulness and impact of the display.

Reconstructing the Pipeline – VISTA Project

In the VISTA project [6] we are working within a consortium of private companies providing utility services (gas, electricity, sewerage, water, telecoms, etc), civil engineering companies sub-contracted to repair and replace these assets, and UK government and industry bodies concerned with the effective management of these services. Data records that describe these utility services are stored and maintained by companies and are the result of surveys in the field and digitized paper plans. This data is used by on-site and back office teams to carry out, broadly speaking, three types of tasks: (a) operational tasks concerned with the delivery of services on a day-to-day basis, e.g. asset detection and new installations; (b) planning tasks concerned with decision making and developing processes and standards, e.g. network and emergency planning; and (c) management tasks concerned with improving performance, e.g. work and asset management and risk assessment.

Changes in surveying and database technologies over the last 200+ years, compounded by major organizational changes within the utility industries, meant that data about buried assets is of highly variable quality and is recorded in disparate formats across multiple databases. Current maps used in fieldwork and planning (e.g. Figure 3 and Figure 4) do not reflect either the quality of the underlying data or its provenance, and this has a major impact on the cost and time taken to carry out streetworks, and on the likelihood of collateral damage. VISTA aims to reduce streetworks and their costs by developing an integrated data model for buried assets, and critically for this context, supporting this integration with visualization techniques that adequately reflect the inherent uncertainty in the data.

Provision

Sources of uncertainty that may be present in utility records include: *error* in digitisation or as a result of data entered incorrectly; *accuracy* which can be absolute or relative (e.g. ±20 cm or within the pavement); *imprecision*: e.g. when using Global Navigation Satellite System (GNSS), the receiver records points over a 24 hour period with measurement precision of ±5 cm; *lineage*: e.g. to describe whether data has been collected using Differential Global Positioning System (DGPS), relative to Ordnance Survey (OS), or hand drawn; *subjectivity* e.g. the construction engineers' notes; and *non-specificity* where an attribute value is known to be one of several alternatives.

Information on positional accuracy is particularly important for asset detection because it allows more informed decisions on the field. The location of assets is often recorded relative to an OS map or control points surveyed sometimes in the past rather than absolute, thus metadata to describe positional accuracy is usually stored in a database. For instance, five confidence categories may be used (from more accurate to less accurate): internal survey, third party survey, indicative, assumed, schematic.

Unfortunately, each organisation has its own confidence classification scheme, which means that although a company can grade the quality of its own data, it has no basis of relating its measures to data from third parties. Moreover, the provision of uncertainty information is patchy – currently not all asset attributes have associated metadata. Uncertainty information is still expensive to capture and difficult to validate.

Depiction

Research carried out in VISTA to visualize uncertainty has focused on the visualization of positional accuracy as this is the source that utility partners expressed most interest in; this is currently also the most articulated source of uncertainty in utility records. We used two popular visual variables to indicate the positional accuracy of assets: *blur* and *colour*. The choice of depiction method was driven by the need for simple methods and visual metaphors suitable for non-technical audiences. [2] suggested that intrinsic methods, such as clarity, are more suitable for non-technical users than extrinsic methods.

Blurring (Figure 5) provides users with qualitative information about spatial accuracy. The more blurred a polyline, the less accurate its position. Our second scheme is the "traffic lights" visualization (Figure 6). It uses a three-colour unified scheme to paint colour bands around utility pipes indicating the confidence in the location of assets.

We encountered a number of issues when implementing the blur method; (a) perceptual issues related to the number of levels that the user is able to distinguish and remember; (b) over-plotting in 2D can result in certain lines looking less blurred or more certain than they are in reality; (c) blurred lines on printed plans may be associated with low quality printing rather than low quality information.

The "traffic light" metaphor is intuitive but mapping different categorizations of confidence from various data sources inevitably introduces inaccuracies, i.e. uncertainty about uncertainty. Another challenge for any intrinsic method to depict uncertainty is how to deal with missing data.

The sparse nature of uncertainty information, the lack of a consistent format for expressing it and the need to accommodate various display media and user expertise all pose a great challenge to the visualization designer as popular methods in the literature cannot be easily adopted in real-life applications.

Usage

The evaluation of the service plans themselves posed a great challenge. The difficulty in this is that plans are a specialised representation. A plan succeeds if the task is performed correctly, e.g. an asset is located without other assets being damaged in the process. In practice however, the value of the plan may be compromised by uncertainties within the data. A "good plan" might none the less lead to task failure. The plan itself is only one part of a large social system, where a "bad plan" may be ameliorated by local knowledge. It is not straightforward to arrange a controlled study. Our argument was probabilistic - by encapsulating accepted good design practice we hoped that the quality of the plans will be improved irrespective of contextual issues; a better plan should lead to a better outcome.

Reflections and Outlook

In contrast to many geo-visualization applications in the literature, there is industrial pressure on utility organizations to show assets visually while at the same time observe established drawing practices (e.g. a recommended colour scheme or line styles for the different asset types). The utility sector has long been working on the subject of standards both with regards to data and symbology. The difficulty, however, is that even something as widely available as standard error bars, for instance, may not be as commonly understood as one might think. This is a clear example of the long running argument between the view of maps as social systems and their view as design artifacts.

Ultimately, utility companies wish to survey assets in the field using absolute rather than relative accuracy; much effort to deal with uncertainty information in the utility sector have been focused on methods to eliminate locational uncertainty via new survey technology. It is not possible to remove all sources of uncertainty from utility data; subjectivity and non-specificity are intrinsic as humans will continue to mediate the provision of data. Moreover, the temporal issue is an important one as there is often a time gap between learning the information and reporting it.

There is much space for improving the way uncertainty information is currently captured, depicted and shared. To make uncertainty visualization successful, there need to be better techniques to capture and model uncertainty data; an agreement on data and implementation; and provision of a socially-agreed system for depiction.

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