Evaluation of the uncertainty-awareness principle using a tumor detection scenario

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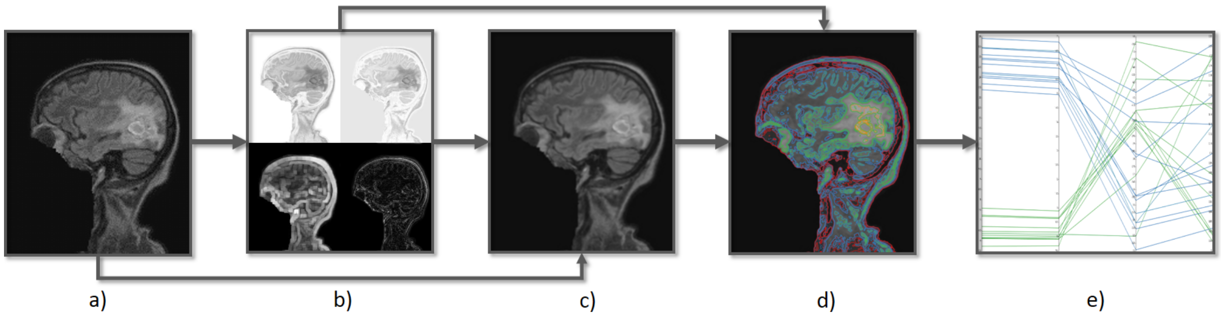

Figure 1: Uncertainty-aware pipeline used for an evaluation of the uncertainty principle. Using the original dataset (a), four different uncertainty measures (b) are being computed. The uncertainty measures and the original dataset are used to smooth the image with an uncertainty-aware gauss filter (c) to reduce noise. The smoothed image and the underlying uncertainty measures are utilized to cluster the image obtaining a weight for each pixel. For these weights an iso-line visualization bordering regions with similar uncertainty behavior can be computed (d). In this visualization, multiple points can be selected by the user to show the respective uncertainty values for each measure in a parallel coordinates plot (e), allowing intuitive exploration of the dataset.

Abstract

The acquisition process of real world data is usually affected by uncertainty, that can have a huge impact for decision making processes. The uncertainty principle tries to address this problem and gives guidelines to quantify, propagate and communicate the uncertainty of a dataset. Although there exist a variety of work that addresses this principle, the uncertainty principle is not evaluated fully. In this work, we utilize a tumor detection scenario from the medical area and applied the uncertainty principle in its entirety. Based on this, we performed a user evaluation that tries to identify the quality of the uncertainty principle in comparison to a standard visualization approach. We summarize the pros and cons of the uncertainty principles according to different measures. Our study shows, that the uncertainty principle helps users to detect the boundary with more certainty and understand the quality of the underlying image data.

Index Terms: Uncertainty—Evaluation—Image Processing

1 Introduction

In a variety of real world applications, state of the art image processing techniques are barley used [7]. This is caused by a variety of factors, where the communication of uncertainty was identified to be crucial [8]. For most of these applications the considered data is affected by uncertainty, which means that measures may vary around the actual measured point [1]. This data uncertainty has a huge impact on the utilized image processing techniques and can cause wrong or miss-leading results for a decision making process.

Clinical image data, such as CT or MRI scans are a prominent example of real world datasets containing uncertainty. Here, a model is used to reconstruct the captured signals to image pixels, thereby introducing uncertainty [14]. In clinical daily routine, medical doctors need to consider these image data to define the actual issue and proceed a suitable treatment.

Sacha et al. [12] formulated guidelines, that need to be fulfilled to promote an uncertainty-aware visualization. In this paper, we aim to evaluate these criteria utilizing a dataset from the medical domain. This evaluation compares the slice-by-slice reviewing methodology, which is utilized in clinical routine, to an uncertainty-aware image processing approach. The approach is composed of uncertainty-aware image processing operations, an uncertainty-aware visualization and an interaction technique. This allows a comparison of the uncertainty principle with a state of the art visualization.

Therefore, this paper contributes:

- An evaluation of the uncertainty-awareness guidelines based on a real world scenario
- A summary of advantages and disadvantages for the implementation of the uncertainty principle

The presented evaluation shows, that the uncertainty-aware image processing approach is helping users to identify interesting areas in the given dataset. The tool also uses a parallel coordinates plot to let the user select distinct points to examine their uncertainty properties. This helps to find out which areas are certain or uncertain.

2 Guideline description

Uncertain data is defined as data that may contain values within some margin of error, which deviates the measured point from the intended or correct result [3]. This effect is caused through the data acquisition process, that is usually a model based reconstruction of sensor captured values.

This work aims to evaluate the uncertainty-awareness criteria originally defined by Sacha et. al. [12]. They proposed four requirements, that need to be fulfilled to achieve uncertainty-awareness in a visualization, namely:

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- **C1** Quantify uncertainty in each point
- **C2** Visualize uncertainty information
- **C3** Enable interactive uncertainty propagation
- **C4** Propagate and aggregate uncertainty

Based on this work, Gillmann et al. [3] identified the clear lack of an implementation for these requirements in open source solutions. Therefore, they proposed a novel data transformation pipeline, that is aware of the uncertainty-awareness criteria C1-C4.

To achieve this, an input dataset needs to be extended by an uncertainty measure (C1). This extended dataset, namely U-dataset is the novel input of an adapted data transformation pipeline. This pipeline (U-Pipeline) is required to not solely transform the data values, but additionally transform the underlying uncertainty information (C4). Throughout each data transformation step, the uncertainty needs to be visualized and interactively explorable by users, while the uncertainty gets propagated to the next pipeline step (C2, C3).

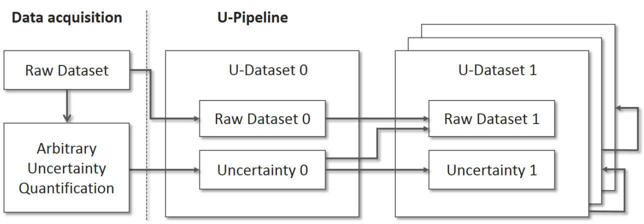

Figure 2: Overview of the U-Pipeline used for the presented evaluation. At first, a raw dataset is utilized as an input. Using the raw dataset, an arbitrary amount of uncertainty measures can be selected by the user to create an uncertainty quantification. Both the raw dataset and the uncertainty quantification are used in the U-Pipeline to apply an operation forming a new dataset. The uncertainty measures influence the outcome of the new dataset in such a way, that uncertain pixels are considered less.

Figure 2 shows the extended data transformation pipeline according to Gillmann et al. [6]. In this paper, uncertainty-aware image pre-processing operations such as histogram equalization, brightness thresholding, clearing areas and detecting edges are presented. Each of these operations are able to transform a U-Dataset in its entirety. These operations can be applied in an arbitrary way, where the output of one operation can be used as an input in the next operation. It is also possible to add, subtract and compare two datasets. This is enabled by the used pipeline witch uses the U-Pipeline to propagate and aggregate the uncertainty measures. This gives every step in the pipeline a distinct U-Dataset, providing the user with the ability to visualize every intermediate step to gain a broad overview over the whole dataset.

3 Experiment

To verify if users will accept and use the uncertainty principle and to determine if this principle improves the decision making process, an evaluation was conducted. In this experiment the U-Pipeline is utilized for a medical dataset. Then the results are compared to a method used in clinical daily routine utilizing a questionnaire. This section presents the results of the evaluation and summarizes the pros and cons while implementing the uncertainty principle.

3.1 Application Scenario

In this experiment a dataset of a human brain with an internal tumor [13] was used. The intention of using that dataset is that a clear border between the tumor and healthy tissue does not exist. In many cases, tumors do not separate clearly from their surrounding tissue. This increases the difficulty for doctors when trying to determine the size, shape and location of the tumor [11]. The dataset also includes two zones of tumorous tissue with a core segment and a surrounding bright area that should both be examined by the user.

As the tumor is not showing clear borders, finding all areas and defining a separation between healthy and tumorous tissue is the main challenge in the presented example.

3.2 Experimental Setup

In order to evaluate the uncertainty principle, defined by Sacha et al. [12], the presented dataset is utilized. We performed a study where users are asked to detect the tumor and its boundary.

We restrict the presented use case to the one slice in Figure 1 a) of the presented data set to exclude interferences of the evaluation results by three-dimensional effects such as visual clutter. In this questionnaire the user is asked to draw the border of the tumor in two different scenarios. First, users are asked to fulfill the task when solely providing them with the slice-by-slice reviewing technique utilized in clinical daily routine. Second, users are asked to fulfill the same task while utilizing an uncertainty-aware visualization approach from Figure 1 d) capable of including all uncertainty awareness requirements (C1-C4). The participants of the presented evaluation were asked to rate the ability of each visualization technique to indicate the tumor boundary. This gives a direct comparison between the slice-by-slice visualization, often used in medicine, and the novel uncertainty-aware visualization. The detailed questionnaire that was utilized can be found in the additional material.

To achieve an uncertainty-aware visualization, the iso-line representation (Figure 1d) given by Gillmann et al. [5], was utilized. The method requires an uncertainty quantification of the input dataset. Here, an arbitrary amount of uncertainty measures can be utilized to output an uncertainty vector for each image pixel. In the presented case we utilized the gaussian error [4], the brightness measure [2], the local range error [15] and the salt and pepper noise [10], as seen in Figure 1 b). These measures were used to create the a U-Dataset. This U-Dataset quantifies the uncertainty in each point, achieving the first criteria(C1) for uncertainty-aware visualization techniques. We applied a gaussian filter in Figure 1 c) to the U-dataset to filter the contained noise in the dataset. Here, the underlying uncertainty was utilized to refine the gaussian filter, such that it considers uncertain datapoints less. This allows a propagation of the uncertainty quantification in the original dataset. While filtering the noise in the original dataset, the uncertainty vectors for each pixel also change, propagating and aggregating the uncertainty vectors for the given transformation (C4). This result is utilized to create the uncertainty-aware visualization presented by Gillmann et al. [5]. The technique utilized iso-lines bordering regions with the same uncertainty behavior, dividing the dataset into similar regions while showing the original slice in the background (C2). In addition, the technique allows a visual exploration of the uncertainty space by allowing users to select specific image pixels and representing the respective uncertainty vectors in a parallel coordinate plot (C3).

3.3 Evaluation Results

We asked 12 persons to participate in our questionnaire based evaluation. The results of this evaluation can be found below.

The age of the attended participants had an average of 27 and we had a ratio of two males over one female. Their working fields ranged from computer science over mechanical engineering to human biology.

At first the participants were requested to draw a border around the tumor on a slice and asked, if they are certain about their decision. For most of the participants it was not clear if they selected the correct tumor border or if they were able to capture all parts of the tumor. This resulted in a mean of 2.2 of 5 points utilizing the Likert

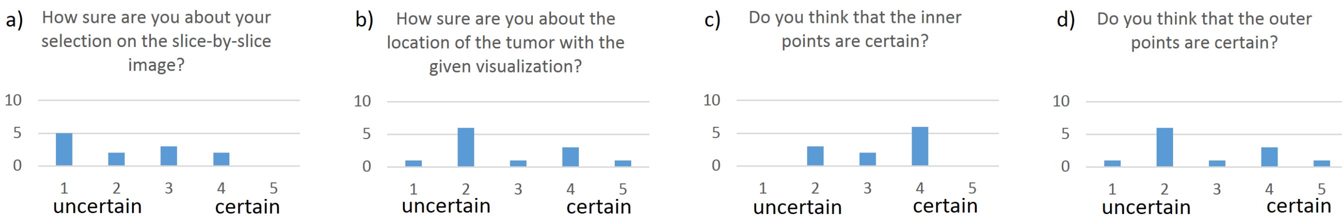

Figure 3: Analysis of the questionnaire result. At first, the participants of the questionnaire were uncertain about the location of the tumor when solely considering the gray scale picture(a) from Figure 1 a). For the proposed iso-line visualization in Figure 1 c) a significant improvement can be achieved (b) where more people were certain about the tumors location. The parallel coordinates view as seen in Figure 1 e) showed that the points on the interior of the tumor boundary are more certain (c) than the one lying outside the boundary (d).

scale. The exact distribution of values can be seen in Figure 3 a). The results show, that defining the tumor border is not an easy task. Considering the fact, that this is an important feature to determine for medical doctors, the importance of this problem becomes clear.

To compare the slice-by-slice method to the uncertainty-aware visualization, the iso-line representation from Figure 1 d) was presented to our participants. The users were prompted to tell how certain they are about the tumors location when considering the uncertainty-aware visualization approach. The mean of the resulting scores given by the users is 3.1. This means an average improvement of 0.9 points to the slice-by-slice method. The exact distribution of the given scores can be seen in Figure 3 b). Since a Shapiro-Wilk test revealed that both data series are not normally distributed (p-value of 0.03528(3a) and 0,01507(3b)), a t-test could not be conducted. But the advantage of this visualization still becomes clear when looking at the average improvement of 0.9 points.

In the last step of the questionnaire, points on the iso-line picture were selected and their uncertainty measures were shown in a parallel coordinates plot. The points where depicted, such that they are located close to the iso-line indicated border of the tumor. Here, some points are located outside the border and some inside the border. Supported by the resulting parallel coordinate plot, users had to state if they think that the inner points (Figure 3 c) and the outer points (Figure 3 d) are certain. For the inner points, people found that they are mostly certain. The outer points on the other hand, were seen as rather uncertain. Here, it becomes clear, that the parallel coordinates view with explicit points is able to indicate the exact uncertainty value of an image point.

In conclusion, it can be seen that the proposed uncertainty-aware visualization is supporting the users to understand the dataset and its uncertainty better, as they can focus on areas with the same behavior under the selected uncertainty measures from Figure 1 b). For the parallel coordinates plot, users found out, that points located inside the tumorous tissue are more certain than the ones outside this region. This information can help clinicians to find regions which could be affected by the tumor, but don't show a clear appearance of tumor tissue.

The proposed use case showed a significant improvement when using an uncertainty-aware visualization. The user study showed that the participants are able to perform a more certain decision making, which is also supported by the following, very motivating statements:

- Areas were grouped together which are not obviously correlated
- Faster decisions can be made
- Objective, absolute and discrete information can be seen
- Similar regions can be seen better

In the medical field of application, tumors and other degenerated tissue often have fluent transitions to healthy tissue. By utilizing uncertainty visualizations, transition zones can be determined and the probability of a data point being affiliated with one or the other tissue can be specified.

The utilized pipeline enables the user to filter noise with different kernels, detect edges by various operators and cut away nonessential information in an easy to use system. Each step in the pipeline can be used by simply applying an operation to one or two U-Datasets. The used operations in the pipeline can be extended as the need for new procedures arise, leaving the user unrestricted.

4 Supporting Elements

Although a medical dataset is analyzed in this work, other data can also be processed with the used visualization by selecting different pre-processing steps and connecting them together. Most kernels and operations can be implemented and used in the pipeline, creating different intermediate steps, which can be combined and compared resulting in a processed image. This processed image can help to analyze the dataset faster.

Uncertainty measures for the uncertainty quantification can be selected arbitrarily, to find the ones giving the most support for the specified task. To find the most useful measure, this high-dimensional space can be visually inspected by looking at every measure one by one. Measures with no direct relation to the given use case can be neglected that way. Even no uncertainty measures can be selected, to adapt to cases where the propagation of uncertainty is not necessary. That means that the underlying U-Dataset can be effectively created and used as desired by the user, as shown in Figure 2.

5 Rejecting Elements

To use the tool on high resolution datasets that origin from new scanning devices, a dedicated infrastructure is required. The used computers have to be capable of computing the required steps in a sufficiently short amount of time while also giving a smooth representation of the dataset. Since computer hardware is becoming cheaper, more compact and powerful, this issue will solve itself over time. In addition, data systems in the respective area need to be capable of saving the additional information generated throughout the uncertainty-aware pipeline (uncertainty-quantification, intermediate computational steps, selections ...).

Another aspect of the needed infrastructure is, that people using the software have to learn how to use it. Users need time to adapt to the new software and techniques used in modern medicine. Here, the educational system needs to be adapted. There exist novel approaches how to teach people theses new skills. One of them is being suggested by Gillmann et. al. [9], presenting a concept lecture aiming to impart image processing and visualization principals for students in medicine.

6 Discussion

To find out if the used tool is powerful and can be used in day-to-day operations, criteria for successful visualizations defined by Gillmann et al. [7] are being tested.

For the usability of the tool, a low difficulty degree for using the visualization and data pipeline is achieved through easy data manipulation. Here, the user has to select an operation and a dataset, to create the next dataset in the pipeline. For any of these datasets, the iso-surface visualization can be created with one button click.

For tool efficiency, namely the consumption of resources, main memory consumption is one of the biggest issues. For every raw data volume, an arbitrary amount of uncertainty measures have to be created as well as for every step in the pipeline. This should be kept in mind when buying dedicated hardware, but will be less important for future applications as computer hardware improves.

The Correctness of a program shows how accurate a visual representation is, while the communication of uncertainty is also required for a good visualization. For the used tool, the communication of uncertainty has been shown before. The iso-surface visualization itself uses this uncertainty information, creating a good representation of the underlying information. For the parallel coordinates view it becomes clear that it shows the exact values of the underlying uncertainty measures.

Flexibility means that different tasks of an application can be executed. This is not solely valid for medical image data, but for every image data that can be loaded as a volume. Any volume can be analyzed and processed, since the user can select the most useful uncertainty measurements for the given application. The pipeline itself is also completely flexible, as any operation can be applied at any time.

The last criteria to be discussed is the intuitiveness of the tool, which declares that the user does not need to have a deeper background knowledge about the programs procedures. Since uncertainty measures have a dedicated representation and every pipeline step can be visualized, the user can find the best visual representation by trial and error.

In the given experiment, only medical image data was examined in order to investigate if improvements can be made in clinical daily routine using uncertainty-aware visualizations. In other application fields, given the error introduced by data acquisition, these techniques can also be applied. Since reconstruction of real world data introduces uncertainty, field experts can use uncertainty information to improve decision-making. Natural disaster forecasts could be made with plans for every scenario and material testing could show points of failure more certain.

7 Implications / Considerations

Our evaluation showed, that the inclusion of uncertainty information is crucial for gaining user acceptance for novel visualization approaches. The implementation of all 4 uncertainty criteria provides a significant improvement in the decision making process. Although requiring a suitable infrastructure and teaching effort, the utilization of an uncertainty-aware visualization is beneficial.

The evaluation of the uncertainty principle also showed, that all four defined requirements for uncertainty-awareness are required and sufficient to achieve an uncertainty-aware visualization.

When implementing the uncertainty-principles to further application scenarios, the following guidelines need to be kept in mind:

- An uncertainty quantification of the utilized dataset need to be found (e.g. high-dimensional data, time-dependent data...)
- An uncertainty-aware visualization, that is able to address the defined requirements needs to be found
- A suitable data management and teaching infra-structure needs to be employed

8 Conclusion

The paper presents an evaluation of an uncertainty-aware data transformation pipeline. This is achieved by using an iso-surface visualization and a parallel coordinates plot presenting the uncertainty information, comparing it to the slice-by-slice visualization used in clinical daily routine. As example data, a brain tumor dataset was being examined by the participants of the questionnaire to quantify the usefulness of the evaluated tool. The results showed an improvement of user certainty when bordering degenerated tissue. The parallel coordinates plot also helped the participants to decide if a region can be seen as certain or uncertain, improving their selection even more.

The overall results show that the embedding of uncertainty-aware data transformation pipelines and visualizations into clinical daily routine is possible nowadays and can help medical doctors to examine data faster and to create better treatment plans.

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