Improving Provenance Data Interaction for Visual Storytelling in Medical Imaging Data Exploration

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Abstract

Effective collaborative work in diagnostic medical imaging is not trivial due to the large amounts of complex data involved, a (non-linear) workflow involving experts in different domains, and a lack of versatility in the current tools employed in healthcare. In this paper, we aim to introduce how the integration of visual storytelling techniques together with provenance data in the analytic systems used in medicine can compensate for these issues, by enhancing communication of results and reproducibility of findings through diagnostic provenance data. To this end, we illustrate how we can improve the interaction with provenance data displayed in a graph in order to facilitate authoring and the creation process of visual data stories.

CCS Concepts
●*Human-Centered Computing* → *Interaction Design; Visualization;*

1. Introduction

Performing data exploration is generally not trivial, especially in healthcare where the data can be complex in nature and structure, and can be large in size. In addition, data analysis is further complicated by the fact that experts in different fields often cooperate on analyzing the same cases through collaborative workflows. As a result, communicating and interpreting results is not always straightforward, and misunderstanding and human errors can occur.

In our study, we focus on visual storytelling for medical imaging data. We have conducted a survey on the radiology workflow to obtain useful insights on needs and concerns of radiologists regarding current IT tools. Building upon already existing toolkits [GLG*16, FSC*06], we developed a prototype of a visual storytelling tool that allows users to perform data exploration and to create visual data stories for presenting the findings based on provenance data of the analysis process in diagnostic medical imaging.

The innovative aspect of our research is the use of visual storytelling based on provenance data for scientific visualization in medical data exploration. According to the respondents and the literature, current software systems lack flexibility in delivering results during both the presentation and exploration stages. Our work ties the information provided by images, user interactions, and exploration findings into a visual story, and thus it creates a clear connection between them. Therefore, the main contributions of the final tool, of which we present here the initial results, are an enhancement of effective communication in cooperative work con-

texts, data reproducibility for informed decision-making, and improvement of collaborative work currently based on text reports.

This way, the level of information details and the complexity of the visual data stories can also be adapted based on the target audience and purpose. For example, users might create more intuitive stories with several frames and descriptive annotations for communication with patients, whereas they might use a lower number of frames and medical jargon for communication with physicians.

We expect that radiologists can reproduce findings during their workflow by interacting with a provenance graph, and present them in a more efficient and visual way. Thus, the provenance graph should enable users in interacting with it in an intuitive manner. This can be achieved by implementing functions aiming at simplifying the provenance data processing based on specific criteria.

2. Related Work

In specifying our model of visual storytelling, we adopted the CLUE (Capture, Label, Understand, Explain) model for data exploration and presentation developed by Gratzl et al. [GLG*16], which consists of three stages: *exploration*, *authoring*, and *presentation*, offering reproducibility of results. A related interesting work is *VisTrails*, a system that provides an infrastructure for recording and visually analyzing provenance data of exploratory tasks [FSC*06, CFS*06, SFC07]. Although the use of visual storytelling in medicine has not been deeply explored yet during the last decade, in contrast with the use of data-driven stories for in-

formation communication in science [SH10, SLRS17], Wohlfart showed how visual storytelling can be associated with volume visualization [Woh06]. Furthermore, several works investigated how provenance data can be used for supporting scientific workflows, how it can be visualized, and how the history management can be improved [HMSA08, SPG05, ABC*10]. Finally, we refer to Ma [Ma99, JKM01], who studied scientific visualization for exploratory purposes and investigated the user interface design space for collaborative settings.

3. Survey: the Radiology Workflow

Meeting with radiology experts and conducting a survey was essential to gather more information and understanding of the workflow in medical imaging. A questionnaire was designed in collaboration with a radiologist and doctor of nuclear medicine, which was composed of 15 questions relating to the following aspects of the radiology workflow:

- Data Used
- Image Assessment
- Data Exploration
- Collaborative Work

The survey was conducted by using the CASI (computer-assisted self-interviews) technique [OHL*12] and 17 international potential users (i.e., radiologists, doctors of nuclear medicine, and residents) participated. The focus was on investigating how radiologists perform medical diagnostic imaging, and how they collaborate with other radiologists and physicians.
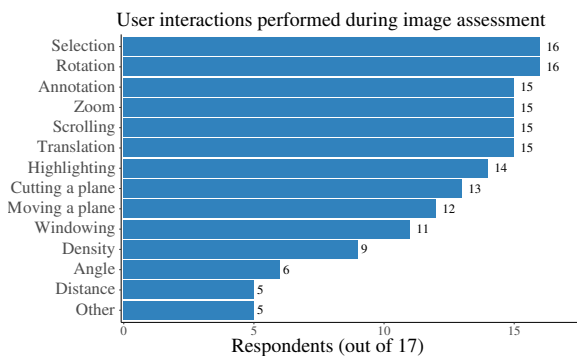

Figure 1: *The histogram of user interactions performed during image assessment according to 17 respondents.*

Data Used. What emerged from the survey is that most of the users analyze complex 3D data (e.g., CT and MRI scans) to obtain different kinds of information depending on the clinical questions. During diagnosis, reference protocols, patient history, and specific meta-data (contrast medium given, slice thickness, type of MRI sequence) are consulted before the image assessment itself.

Image Assessment. The typical working procedure starts with arranging the given images, performing some windowing, zooming and measurements, and preparing a (structured) text report.

Data Exploration. The most common user interaction techniques used are selection, rotation, annotation, zooming, scrolling, translation, and highlighting as shown in Fig. 1.

Collaborative Work. Furthermore, according to the respondents, collaborative work can be improved by associating key images and measurements with the structured reports to make them more easily-retrievable (e.g., by using hyperlinks).

Finally, automation in structure recognition, measurement systems, report compilation, and windowing is also urgently awaited by some respondents to lighten the individual workload.

4. A Visual Storytelling Tool for Medical Imaging Data

After conducting the survey, we define the main features of the envisioned tool as well as specific elements of the provenance graph.

4.1. The Main Features of a Visual Storytelling Tool

Medical imaging is usually employed in multi-disciplinary environments where many kinds of data should be processed, and experts with different specialized and technical knowledge have to collaborate. First of all, the data exploration of 3D images can be performed as illustrated in Fig. 2.

The figure shows an overview of our prototype built upon the Phovea framework [GLG*16] and the AMI toolkit [FNN] used for exploring brain image data. It can be seen how the main window for the 2D and 3D data exploration (on the left side) is supported by two widgets for changing the settings and for retrieving provenance data. This is visually represented by an ordered tree with multiple branches and thumbnails (on the right side).

On top of that, an authoring tool should be integrated to enable making annotations about exploration discoveries on the data itself. Along with this, provenance data for the visual exploration can be collected and visualized in an interactive provenance graph, providing information about the analysis process made by the user(s) and for reproducing particular steps of the analysis. Moreover, the tool is equipped with a presentation mode to fully incorporate the visual storytelling concept. Users can present final and partial results to various audiences, through a sequence of visualizations and using a variety of available visual storytelling techniques [SH10, HMSA08].

4.2. User Interaction with the Provenance Graph

Since many considerations have to be made before achieving our ultimate goal of developing a validated visual storytelling tool, we started focusing on the user interaction with the provenance graph, which is a key element of our project. Navigating through an interactive ordered tree including multiple branches for each different exploratory decision and user, it is possible to extend/author the data exploration and to adjust it an unlimited number of times at any phase of the analysis.

In developing an interactive tool and its features, a set of rules should be defined in order to build interconnected functions upon them. Since we aim to give users more flexibility, allowing them
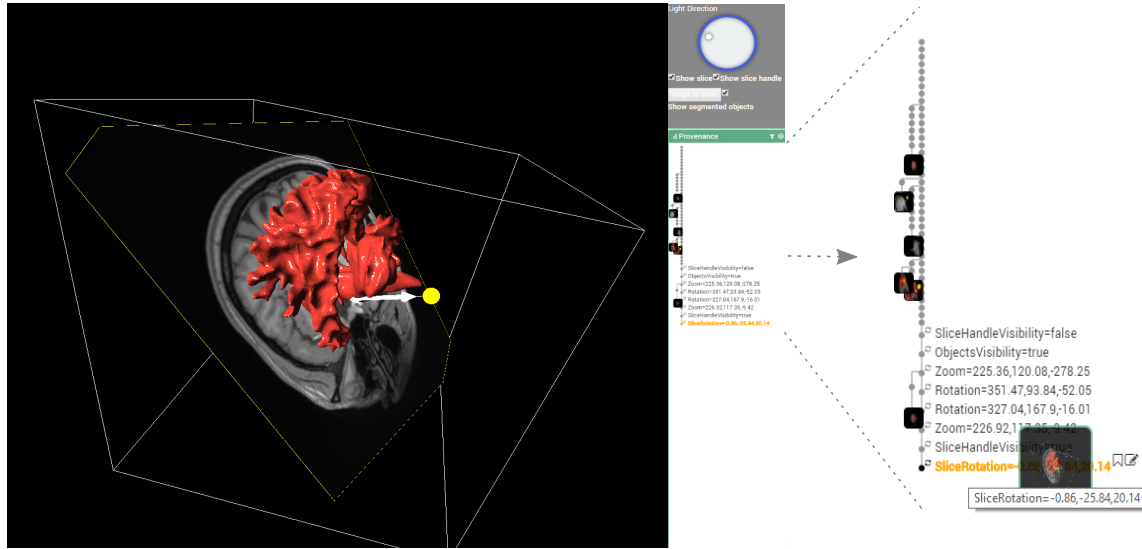
Figure 2: *Left: Overview of our visual storytelling tool with a main window for 2D and 3D data exploration, one widget for changing the settings, and one widget for provenance graph interaction. Right: A provenance graph with multiple branches, thumbnails of the main window in the end-nodes, and image preview and details on-demand (the highlighted end-node).*

to choose at which level of granularity (or abstraction) the provenance data should be represented, we considered two well-known approaches which illustrate taxonomies to categorize user interactions. Shneiderman defined *a task by data type taxonomy*, which became a landmark model in Information Visualization [Shn96], whereas Yi et al. stressed the relevance of *user intents* in categorizing user interactions [YAKS07].

However, our scenario is slightly different since we are in a visual storytelling context where user interactions for authoring play a crucial role. Therefore, we assume that the user intents considered for their categorization are also different. Based on the survey results and adapting the existing taxonomies to our situation, we envision the process of 3D data analysis by visual storytelling tools as a (non-linear) sequence of user interactions to configure, explore, select, derive information from, and annotate the input data. Thus, we obtained six (non-exhaustive) classes of user interactions:

- *Configure* (e.g., show the rendering, switch from 3D to 2D view)
- *Explore* (e.g., rotate, zoom, translate the slicing plane)
- *Select* (e.g., highlight or select a specific area)
- *Derive* (e.g., measure a distance or an angle)
- *Annotate* (e.g., make annotations)
- *Provenance* (e.g., provenance graph interaction)

Whereas *Explore* and *Select* do not need further description, we grouped under *Configure* all the interactions related to 3D data visualization and its configuration. The classes *Derive* and *Annotate* include all the user interactions which lead to making measurements and annotation during data exploration, while the *Provenance* interactions are those related to the provenance *graph* interaction.

Hence, we define four grouping strategies, each corresponding to a certain level of abstraction, for provenance graph nodes:

- *no grouping applied* (i.e., all the single user interactions are shown)
- *per parameter change* (i.e., only user interactions with parameters significantly different are shown)
- *per user interaction* (e.g., rotation, zoom, highlighting)
- *per user intent* (e.g., *Configure*, *Explore*, *Select*)

We first illustrate this on a simple example in Fig. 3. A provenance graph shows that three rotations were sequentially performed, and among them, the first and second ones were not significantly different in terms of parameter (angle) change. Then, zoom and highlighting were also performed. We omit an explanation of how to define the thresholds, as this is out of the scope of this work. Thus, *grouping* not only depends on the user interaction categories, but also on the level of abstraction chosen.

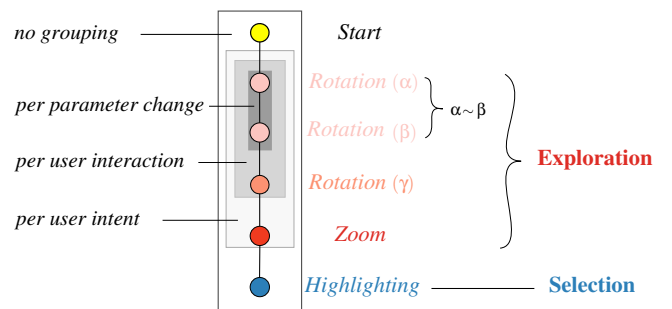In case of grouping per user intent, only two nodes would be

Figure 3: *A visual explanation of how data would be visualized at different levels of abstraction (i.e., no grouping, per parameter change, per user interaction, and per user intent), where the color encoding represents the category of nodes.*
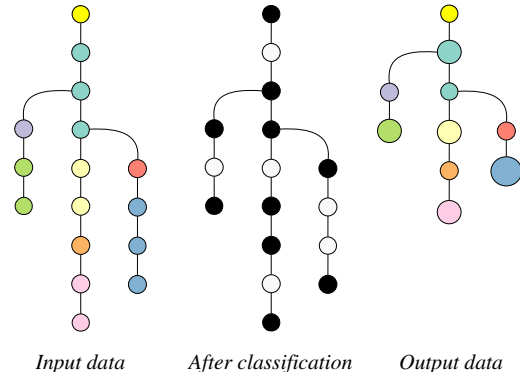
Input data   After classification   Output data

Figure 4: *A visual representation of how input nodes (left) are classified (center), and then grouped (right). The color encoding in the first (left) and last (right) graph represents the (arbitrary) class of nodes, whereas in the central graph, black nodes are* key nodes*, and white nodes are* regular nodes*. The node size on the right encodes the number of nodes grouped.*

shown after the initial status: one for representing *Exploration*, and one for representing *Selection*. In contrast, three nodes would be shown after grouping per user interaction: one per rotation, one per zoom, and one per highlighting. Finally, only nodes representing user interactions not significantly different in terms of parameter change would be collapsed in the low-level scenario.

However, if we consider more complex cases, some additional rules must be set. As an example, an ordered tree with multiple branches and with nodes belonging to different classes (encoded by color) is illustrated in Fig. 4, left. Since we aim to reduce the information overload in the provenance graph, only nodes relevant for data exploration and (visual) data story creation at a certain level of abstraction should be visualized. To this end, we classify all nodes in the provenance graph into two categories: *key nodes* (marked by ●) and *regular nodes* (marked by ○), as illustrated in Fig. 4, center. The *grouping* function should not group two or more key nodes. Thus, we define a key node as any node of the following mutually exclusive node types:

- *Root* (i.e., the starting node of the provenance graph);
- *Leaf* (i.e., a node with no children);
- *Subroot* (i.e., a node with more than one child);
- any other node with interaction of a different class to its child's.

The remaining (regular) nodes are considered non-informative, and are grouped downwards onto a key node; see Fig. 4, right. The node size encodes the number of nodes grouped. This algorithm works independently of the level of data granularity, so it can be applied with different levels of abstraction.

5. Discussion

The conducted survey provided a starting point for outlining the main features of a visual storytelling tool that can compensate for the lack of flexibility in authoring and presenting findings of current tools. As described by the survey respondents, they lack an efficient system for communicating effectively and for collaborative work.

We consider the survey results reliable because of the sample size (i.e., more than 15 participants).

Using a visual storytelling framework based on provenance data in combination with user interaction techniques for exploration of complex data, research findings can be validated with evidence and previous analyses can be retrieved, reconsidered, and reused during future assessments. In this way, the risk of encountering human mistakes in the decision-making process due to misunderstanding or incorrect interpretation of results can be decreased. According to the potential users' statements, our prototype meets the initial requirements since it allows other doctors to understand and agree on the conclusions drawn by the investigating doctor. In addition, integrating the visual storytelling concept into traditional imaging data exploration seems to be promising for replacing text reports.

Furthermore, outcomes of medical diagnoses will become more reliable even in a collaborative setting context, since they can be linked back to (provenance) data and authors that generated them. We believe that the *grouping* function is crucial for the story creation process to offset the large amount of data available and the unrepeatability of analysis steps. Combined with different levels of granularity of the visually represented provenance data and with the associated user interaction categories, it can facilitate users to interact with their (non-linear) analysis process during both data exploration and data story creation. Additionally, color encoding and thumbnails can also improve the provenance graph interaction in both the exploration and presentation stages.

6. Conclusion and Future Work

In the last years, many efforts have been made in investigating the application of visual storytelling techniques in science. Although we are still in an exploratory stage, there is evidence of the beneficial effects of storytelling for data presentation, and of a need to improve communication in collaborative work settings. This has been confirmed by survey results regarding radiology as field of application. Based on this and on previous works, we outlined a visual storytelling tool aiming to compensate for flaws and deficiencies of the current tools used for diagnostic medical imaging.

In future work, we aim to extend our method. We plan to perform a user study to learn more about user intent and to potentially refine the taxonomy of user interactions. Furthermore, evaluating the effectiveness of the tool, and the individual effects of its current features (e.g., how much information is lost per *grouping* at different levels of abstraction) as well as novel ones such as merging branches based on some of the above-mentioned rules is our next objective. Although the initial case study is radiology, the tool has not been envisioned as domain-specific and it is easy to generalize (e.g., using different features, taxonomies, and levels of abstraction). For this reason, we want to investigate differences in the visual storytelling tool settings for different domains, and the contributing factors of specific application scenarios.

7. Acknowledgements

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