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Communicating Pathologies and Growth to a General Audience

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Abstract

In this paper, we investigate the suitability of different visual representations of pathological growth using surface models of intracranial aneurysms and liver tumors. By presenting complex medical information in a visually accessible manner, audiences can better understand and comprehend the progression of pathological structures. Previous work in medical visualization provides an extensive design space for visualizing medical image data. However, determining which visualization techniques are appropriate for a general audience has not been thoroughly investigated.

We conducted a user study (n = 60) to evaluate different visual representations in terms of their suitability for solving tasks and their aesthetics. We created surface models representing the evolution of pathological structures over multiple discrete time steps and visualized them using illumination-based and illustrative techniques. Our results indicate that the suitability of visualization techniques depends on the task at hand. Users' aesthetic preferences largely coincide with their preferred visualization technique for task-solving purposes.

CCS Concepts

• *Applied computing* → *Life and medical sciences;* • *Human-centered computing* → *Scientific visualization;*

1. Introduction

Various pathological conditions undergo changes over time, often showing growth within the human body. Understanding and communicating these temporal changes to an audience with potentially limited health literacy is a challenging task. However, since the growth of pathological structures is essential for treatment planning and outcome predictions, communicating it to a general audience facilitates informed consent as a patient and can be used to promote prevention, such as regular screening for certain diseases. In this context, narrative medical visualization with its focus on engaging, memorable, and comprehensible visualizations enriched with textual information is promising to effectively communicate complex medical data to a general audience of non-experts [MGS*22]. By combining appropriate data visualization and interaction techniques with storytelling elements, medical professionals and educators can empower non-experts to understand complex medical data, facilitating informed decision-making, health literacy, and patient engagement.

For medical data communication, appropriate data visualization and interaction techniques must be employed. Visualization techniques that emphasize the temporal dimension can help illustrate the progression and growth of pathological conditions over time. Interactive features such as annotations, navigation buttons, or rotatable objects allow viewers to explore the data at their own pace and focus on specific details of interest. However, they need to be carefully designed to be feasible for a broad audience.

In this study, we investigate the suitability of different representations for morphological growth. For this purpose, we use surface models of intracranial aneurysms as well as liver tumors, representing their evolution over several discrete time steps. The models were rendered using three different techniques, namely Phong, outlines, and Fresnel combined with hatching lines. We also compared the visualization of all time steps side-by-side versus successively. We chose aneurysms and liver tumors because we have both data sets and experience working with these pathologies. Tumors in general are a well-known disease that show pathological growth over time. In contrast, aneurysms are less well-known but have different growth patterns. While tumors often grow in all dimensions, aneurysms tend to have a more distinct direction of growth. In a user study with 60 participants with varying medical expertise, we compared our visualizations in terms of their ability to assess growth processes as well as their aesthetics. In summary, our study contributes:

This paper makes valuable contributions to the field of medical visualization by conducting an evaluation of well-established techniques with a diverse audience, encompassing varying levels of health literacy. It provides insights into the convergence and divergence of visual preferences among non-expert users and their performance in solving tasks using different visualization styles. By exploring the feasibility of visualizations to effectively convey growth in medical image data, the paper offers practical recommendations for conveying complex medical concepts to a broader au-

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dience. The findings and discussions presented in this paper serve as a foundation for enhancing the design and implementation of medical visualizations, ensuring they are accessible, engaging, and informative for a general audience.

2. Related Work

In this section, we discuss existing research on narrative visualization and its application to medical data communication, as well as visualization of temporal changes. These studies provide a foundation for the current research and highlight the gaps or opportunities that the current study aims to address.

2.1. Previous Studies on Narrative Medical Visualization

Several studies have examined the use of narrative visualization techniques in various domains, including healthcare and medical communication. The majority of research in this domain has primarily focused on information visualization [GP01, TRB*18]. Höhne [Höh97] presented a first approach for interactive analysis of CT data by the general public in the context of a museum exhibition. Wohlfahrt and Hauser [WH07] designed an authoring tool for generating medical data-driven stories to increase the comprehensiveness when presenting medical volume data. Garrison et al. [GMF*21] investigated the preferences of experts and non-experts regarding the visualization of biomedical processes. Their results show that preferences depend on the level of expertise of the target audience. Users without domain expertise particularly disliked distracting or excessive visualizations. However, neither experts nor non-experts preferred extreme realism or extreme abstraction. Both groups valued visualizations that met the stated communication objective. For our target audience of non-experts, we use simple semi-realistic and illustrative visualizations for our study. In contrast to the work of Garrison et al., we focus on a specific communication objective and thus use tasks to test whether the stated user preferences match their performance in solving the tasks with a given visualization technique.

Meuschke et al. [MGS*22] conducted a study on how narrative visualization can be used to communicate disease data to non-experts, highlighting the improved comprehension and engagement of participants compared to traditional data presentation methods. Aesthetic aspects, such as an attractive and consistent design, play a crucial role. Similarly, Kleinau et al. [KSM*22] and Mittenentzwei et al. [MGM*23] explored the influence of using the narrative genres *slideshow* and *scrollytelling* for disease communication on usability and aesthetics. Mittenentzwei et al. [MWS*23] explored the impact of distinct human protagonists, including a patient and a physician, on users' trust, identification, and engagement with a narrative medical visualization. These manuscripts focus primarily on how to build and structure a data-driven story but do not explore which visualization techniques are appropriate for presenting medical data to a general audience.

2.2. Medical Visualization for Surface Models

There are various options to visualize surface models of anatomical and pathological structures in an expressive manner that conveys their shape. An essential prerequisite is to smooth surface models to compensate for staircase artifacts that result from the limited spatial resolution and the anisotropic character of medical image data. Simple mesh smoothing approaches, however, lead to the loss of details and volume. Bade et al. [BHP06] conducted a comparative study to assess the effectiveness of various mesh smoothing approaches in preserving anatomical shape features, using a tumor as an example. One essential smoothing method restricts the displacement of vertices to one diagonal of a voxel [Gib98]. Moench et al. [MAP10] minimized the negative effects of smoothing even further by restricting the displacement of vertices to those heavily affected by the anisotropic resolution. Their method was primarily used to smooth tumor models and present them in their surroundings. Later, Wei et al. [WZY*15] presented methods to better preserve the shape features of anatomical structures. The most recent methods towards this goal are based on deep learning [WWG*18]. Smoothing is particularly important for illustrative surface visualizations since these emphasize discontinuities of surface models. It would be misleading if these discontinuities represent artifacts instead of relevant shape features. For vascular structures, special techniques were developed based on implicit surfaces aiming at a comprehensible rendering of their branching patterns [SOB*07].

Illumination-based techniques, like Phong, mimic the physical effects of light and create depth cues by adding highlights and shadows depending on a present light source [PBC*16]. Thus, more realistic visualizations can be created. Phong shading is a basic shading technique, often used for comparative evaluations of state-of-the-art methods [LLPH15].

Illustrative rendering techniques are inspired by scientific illustrations [LSBP18]. They can be used to simplify visual representations through abstraction, reducing the visual clutter of a scene [VI18]. Essential illustrative rendering techniques are silhouette rendering, rendering of other feature lines, stippling, and hatching. Illustrative rendering can be integrated into direct volume rendering [BG07, RBG07] or in surface rendering, which is more essential for this paper since we display surfaces of segmented anatomical and pathological structures. The realization of silhouette rendering and its integration with surface rendering was described by Tietjen et al. [TIP05] and employed for visualizing tumors within the liver. Lawonn et al. [LMP13] presented a method that integrates silhouettes and hatching lines. Later, they also evaluated their methods with respect to their effect on shape perception [LBSP14]. There are various visualization techniques that can be categorized as silhouettes, contours, feature lines, stippling, hatching, shading, etc. [LVPI18].

2.3. Visualization for Longitudinal Medical Image Data

Researchers have developed a range of techniques to capture and communicate changes over time in the field of visual analytics [AAD*10]. Zhang et al. [ZCD19] apply these techniques to the healthcare domain and highlight the importance of linked views. Accordingly, we have linked our visualizations of the different time steps, so that the rotation of one surface model is followed by the rotation of all other surface models.

Visualizing longitudinal medical image data supports clini-

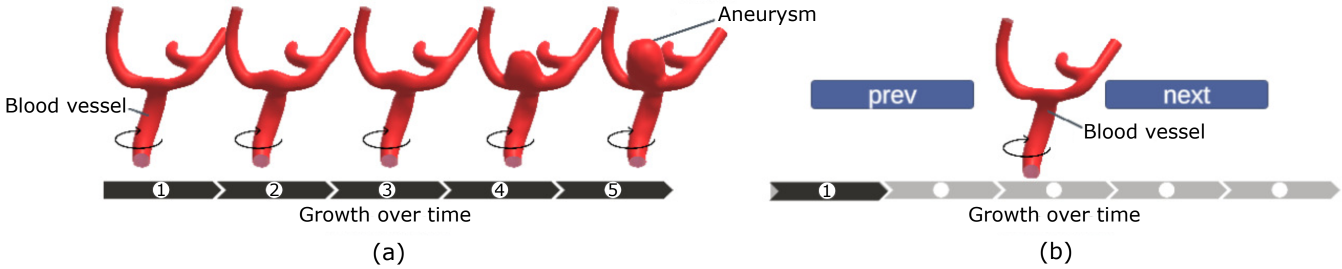


Figure 1: *We offered two alternatives for displaying the time steps: (a) all time steps are displayed simultaneously next to each other, and (b) the time steps are displayed successively and can be controlled by the user via buttons.*

cians in the assessment of treatment response and patient prognosis [GOP*13]. To enhance a visual comparison of different time steps, registration of the data sets is necessary. However, registration remains a challenging task, even using advanced deep learning techniques such as deep learning [FLW*20]. Sugathan et al. [SBR*22] visualized longitudinal brain lesion evolution of patients with multiple sclerosis. They focused on visualizing the lesions using contours and meshes. They showed the different time steps side-by-side and in an overlay view. We followed a similar approach by visualizing time steps side-by-side.

In contrast to studies that use longitudinal image data, tumor growth models provide a way to mathematically model the expected evolution of a tumor [SSB21, PTZ21]. A similar approach has been investigated for aneurysms [AKA*20]. The predictions are used for treatment planning and prognosis.

3. Medical Data Sets

We chose intracranial aneurysms and liver tumors as medical examples of pathological growth over time. The first disease is an example of a vascular disease and the second disease represents tumor diseases, including cancer. About 3% of the adult general population is affected by saccular unruptured intracranial aneurysms [HTKR21]. Liver cancer is the fifth most common cancer and is responsible for 8.2 % of cancer deaths worldwide [SSD04].

Intracranial aneurysms are local dilations of blood vessels in the brain. They rarely cause symptoms but are at risk of rupturing and causing life-threatening intracranial hemorrhage. Aneurysms can grow and change shape over time, which is often considered a sign of increased risk of rupture [NY17]. Because treatment of aneurysms carries its own risks, including rupture, many aneurysms that are considered stable (no enlargement >0.5 mm for at least 9 months) are not treated. However, it is important to monitor aneurysms over time to assess the risk of rupture, as even stable aneurysms can become unstable after several years [SKT*16].

Unfortunately, there are few long-term data sets on the natural history of aneurysms. Many patients opt for treatment or do not return to the same hospital for regular follow-up. Since we did not have longitudinal data from multiple patients collected at different points in time, we created artificial time steps. Therefore, we used surface models derived from real medical image data and altered them using the 3D modeling software *Blender*. Thus, we also avoid the challenging registration problems that would occur if we would employ medical image data. In this way, we created up to five different alternations of each model showing how it might have looked as it grew. One of these artificially generated steps is always the healthy vessel before the development of the aneurysm.

As a second example, we focus on liver tumors. Like aneurysms, liver tumors rarely cause symptoms. In advanced stages, liver cancer can cause symptoms like weight loss, a loss of appetite, and pain [LY17]. For tumors, either curative or palliative treatment is provided soon after initial diagnosis [LCC15]. Similar to the aneurysm data, we have generated the time steps between a healthy liver and the original tumor data set artificially by shrinking the tumor several times to create five time steps.

We used six data sets of intracranial aneurysms and four data sets of liver tumors. The artificially generated time steps do not depict how the structures actually changed over time. The primary goal is to educate an audience of non-experts about general concepts, thereby mitigating the strict need for absolute accuracy. Nevertheless, we advocate the use of authentic data whenever possible. It is important to emphasize that the creation of synthetic time steps is a resource-intensive process that requires the expertise of both a visualization or design specialist to create the 3D models and a medical expert to assess the credibility of the artificially formulated data before it is suitable for practical medical briefings. This is especially true the more complex the surface. Both aneurysms and tumors can develop bulges called blebs. Malignant tumors in particular often have complex growth patterns with more growth near blood vessels, which is very difficult to model artificially. While we chose to generate additional artificial time steps due to the lack of real data, the results of our study are applicable to similar authentic data sets.

4. Design Decisions of the Study

The design space for visualizing changes in medical data sets is vast and we do not intend to cover it comprehensively with our study. Rather, we wanted to do an initial exploration of different style directions, namely illumination-based and illustrative methods, to get a direction for future design studies. Common techniques for enhancing shape perception are shading (such as Phong or tone shading), feature lines, textures, and boundary emphasis [PBC*16]. From this set of categories, we chose Phong shading as an example

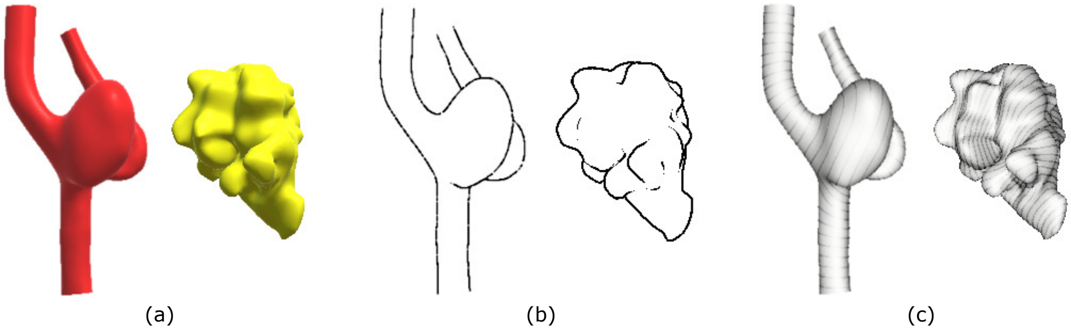


Figure 2: *Different visualization techniques for the aneurysm and tumor surface models. (a) shows Phong shading, (b) inverted hull outlines, and (c) a combination of a Fresnel shader and hatching lines.*

of shading and outlines as an example of boundary emphasis. We decided to enhance the outlines with view-dependent feature lines to visualize the ridges and valleys of the surfaces. Hatching is an example of textures. However, we found that hatching lines alone were confusing to the participants, especially for small shapes like the first time steps of the tumors. Therefore, we combined them with a Fresnel shader to improve the participant's ability to identify the anatomical shapes. We focused on introducing a semi-realistic illumination-based shading (Phong), an illustrative technique (outlines), and a combination of a semi-realistic shader with an illustrative technique (Fresnel shader combined with hatching lines).

4.1. Implementation of the Visualizations

We implemented our visualizations in Unity 2021.3.7f1. Unity provides many prebuilt interaction techniques and shaders to help programmers efficiently implement interactive visualizations. Unity's built-in visual scripting for shader implementation, the Shader Graph, allows for the quick creation of simple shaders such as Phong and Fresnel shaders. Materials can be easily generated from shader files and applied to 3D meshes in the scene. Parameters, such as color or brightness of the material can be adapted in the visual inspector or on run time. Unity's interface allows meshes to be arranged in a hierarchy where transformations applied to a parent automatically affect all of its children. Furthermore, Unity provides pre-built UI elements, such as drop-down menus and toggle buttons. This enables to quickly build an interactive three-dimensional scene using the visual editor.

4.2. Presentation of Time Steps

We display five time steps for each data set in two variants, see Figure 1. The first is to display all time steps simultaneously side by side. This way a user can see all time steps at a glance. The second variant is to display the time steps successively. The user can switch to the next or previous time step using buttons. The surface model of each time step is replaced in place. We decided to give the user the ability to control the visualization instead of creating an automatic animation to allow them to analyze the data at their own pace. Both variants were visualized using different shaders as described in the following sections. Other techniques, such as overlaying multiple time steps, would also be possible. However, the surface models of later time steps are usually larger in all dimensions and would completely encapsulate models of earlier time steps, making them impossible to see. A possible solution would be to make larger objects semi-transparent. However, we decided against this approach because transparency would introduce a new dimension into our design space.

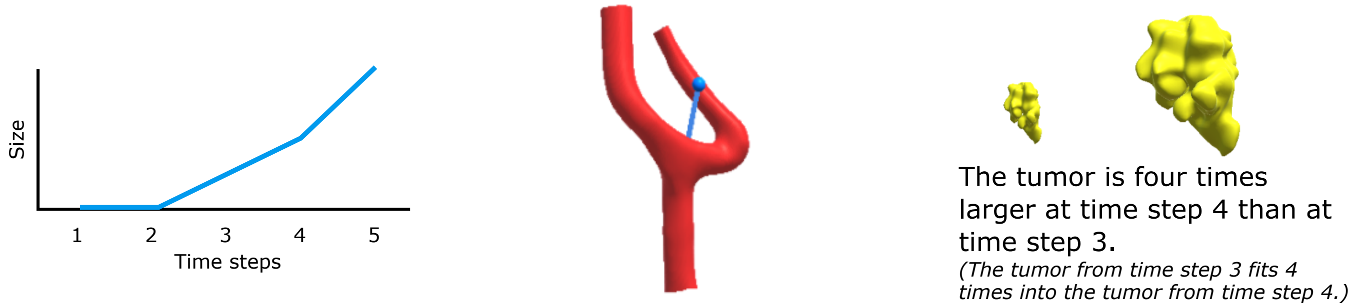
In our evaluation, we have decided to use five time steps. On the one hand, we considered the task of differentiating fewer time steps to be too simple, and on the other hand, adding additional time steps would increase the participant's processing time due to the additional time spent on analyzing all given time steps. We considered five to be a good balance between task complexity and a participant's processing time.

4.3. Semi-Realistic Visualization

We opted for a semi-realistic representation of the surface models using a Phong shader to add highlights and shadows to our surface model, see Figure 2 (a). We chose red as the color for the aneurysm data sets because it is the most intuitive color for a blood vessel. We colored the tumors yellow to provide a good contrast to the surrounding vascular tree and liver tissue, which are colored in various shades of red. Using a simplified, semi-realistic representation of the anatomical structures, our goal was to make the visualization more accessible to a general audience of non-experts. While realistic medical footage is often considered gross by many non-experts, our simplified models depict anatomical structures using conventional colors (e.g., red for blood vessels) without being disturbing to the viewer.

4.4. Illustrative Visualization

In addition to the semi-realistic approach, we also implemented a fully stylized illustrative visualization, see Figure 2 (b). To do this, we used an outline shader that follows the principle of an inverse hull shader, where the object is rendered using a multi-pass approach [RC99]. In the first pass, the object is rendered with an unlit white shader. Then the outline is created in the second pass by scaling the object up slightly and rendering only the backside of the larger model in black. The thickness of the outline depends on the scaling factor applied to the larger model. The result is an illustrative visualization reminiscent of a simple pencil drawing.



(a) Estimating growth rate (b) Estimating growth direction (c) Estimating size difference

Figure 3: *Examples of the three types of tasks the participants were asked to solve. (a) shows a piece-wise linear function depicting the growth rate. (b) marks the growth direction using a pin. (c) shows the description of the difference in the size of two adjacent time steps. The tasks were designed as multiple-choice questions, where users were presented with three different alternatives per task type and had to choose the correct one.*

Age	
18-25	25
26-35	23
36-45	4
46-55	1
56-65	5
>65	2

Gender	
Male	23
Female	31
Diverse	5
No answer	1

Education	
Pupil (no graduation)	5
High school diploma	19
Vocational training	3
University degree	33

Professional contact with medical topics	
Never	18
Rarely	9
Sometimes	10
Often	7
Very often	16

Professional contact with 3D visualization	
Never	30
Rarely	5
Sometimes	12
Often	7
Very often	6

Table 1: *Participant metadata.*

4.5. Semi-Realistic Visualization with Illustrative Aids

For our third visualization style, we combined a semi-realistic approach with illustrative aids to investigate whether a combination of the two techniques provides better support for exploring the data. Therefore, we used a Fresnel shader to create depth cues similar to the Phong shader. We included grey hatching lines as an additional visual aid to show the surface curvature, see Figure 2 (c). We chose to use a Fresnel shader to create a color shift from white to grey to keep the color scheme of the illustrative technique. The Fresnel shader was also applied to the hatching lines to make the end result look coherent.

5. Evaluation and Results

Using the *Long Night of Science*, an annual event where the university showcases its research to the local public, as well as the university mailing list, we gathered 60 participants. We conducted a comparative, between-subject user study to evaluate the visualization techniques. We set up an online study, where each user had to solve twelve tasks for the aneurysm data sets and twelve tasks for the tumor data sets. For each data set, users were required to complete tasks and indicate how confident they were in their answers. The study ran for about one month.

5.1. Participants

We asked participants about their age, gender, highest education degree, and professional experience with medicine and three-dimensional visualizations, see Table 1. Most of the participants (87%) are 35 years old or younger. About half of our participants are female (52%), and six participants are diverse or preferred to not answer the question. Half of the participants stated to never dealt with 3D visualizations professionally. 16 participants (27%) stated that they deal with medical topics very often and seven (12%) said often. Thus, a large part of our participants have a high medical literacy. 50 participants (83%) are from Germany. None of our participants is colorblind.

5.2. Study Design

We created six evaluation sequences by presenting the visualizations to study participants in different orders to minimize bias. The same visualization techniques are always shown in two sequences but in different order. Each participant saw only one of the following sequences:

1.1 Phong starting with a side-by-side view
1.2 Phong starting with a successive view
2.1 Outline starting with a side-by-side view
2.2 Outline starting with a successive view
3.1 Fresnel with hatching starting with a side-by-side view
3.2 Fresnel with hatching starting with a successive view

Each sequence was evaluated by ten participants. Therefore, each visualization technique was evaluated by 20 participants. We have been particularly careful to avoid our results being falsified by the occurrence of a learning effect or by pairing easier or more complex data sets with a certain visualization technique. Therefore, we chose to show each of the three visualization techniques (Phong, outline, and Fresnel with hatching) to only one subgroup. All participants see the same medical data sets. To be able to compare

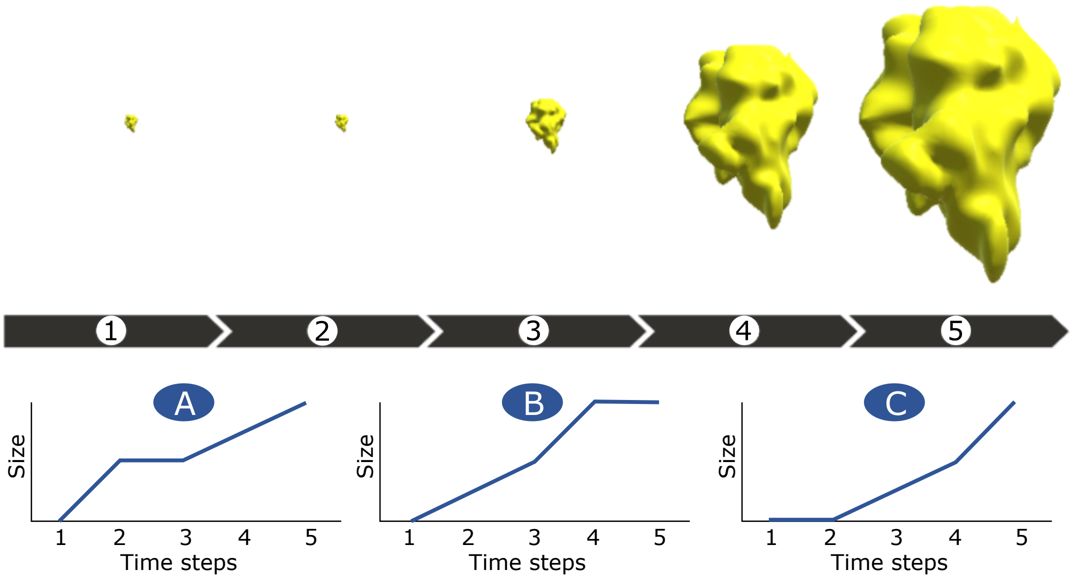


Figure 4: *Excerpt of our user study. Users are presented with different time steps that can be explored using rotation. The models are linked, meaning that a rotation of one model automatically rotates the other models in the same way to facilitate their comparison. Users are asked to choose the correct answer out of three options.*

the presentation format of the time steps (side-by-side and successively) without a learning bias, we created two evaluation versions per visualization technique, one starting with the side-by-side views and one starting with the successive presentation.

5.3. Tasks

We selected three types of tasks for participants to complete, see Figure 3. We chose a multiple-choice approach, where the users had to select the correct answer from three options. For the aneurysm data sets, the users had to identify the growth rate over all time steps as well as the growth direction, which we identified as key characteristics for aneurysm growth. Since tumors often do not have a clear growth direction, but expand in multiple directions, users had to identify the growth rate as well as the size difference between two time steps for each tumor data set. For each selected answer, the users had to indicate how confident they were. For this purpose, we used a 5-point Likert scale ranging from *very confident* to *not confident at all*. Finally, users were asked whether they preferred the simultaneous or successive depiction of the time steps for solving the tasks and for aesthetics.

In the following, we describe the design of the multiple-choice tasks in more detail. For each type of task, we had three levels of difficulty. With which level of difficulty participants start is randomized. Furthermore, it is randomized, in which concrete answer options are presented to a participant, and which of the options is correct and is displayed with the respective models. At the beginning of the evaluation, the participants are presented with an example task of medium difficulty.

Growth Rate. The participants were asked to determine the growth rate over all time steps. Therefore, they had to choose the function depicting the correct growth rate from three options, see Figure 3 (a). Beforehand, we rated the answer options according to their difficulty level which depends on the number of linear segments in a piece-wise linear function as well as plateaus. This means, that the level of difficulty is based on how many times the growth rate changes over all time steps of one data set. Plateaus are especially easy to identify, therefore, they build an exception to this rule. In summary, easy growth rates contain either two plateaus or are a linear function, while growth rates of medium and high difficulty contain one plateau at most and consist of three linear segments or more than three linear segments, respectively.

Growth Direction. To determine the growth direction, users had to choose one out of three models of the blood vessel. The aneurysm is replaced with a pin showing the main growth direction, see Figure 3 (b). Again, the solutions were classified into three levels of difficulty. False answer options where the direction of growth differs by at least 40 degrees in all three directions from the correct answer are labeled as easy. False answer options of medium difficulty differ only in two directions from the original and false answer options of a high level of difficulty differ in only one direction from the correct answer. We decided on 40 degrees after testing different values. In our examples, 40 degrees is a deviation that is not too easy to detect, but also not too close to the actual alignment.

Size Comparison. To evaluate how well the users can identify the change of volume, they are presented with a subset of two consecutive time steps for each tumor data set, see Figure 3 (c). Then the task is to determine their difference in size. For the first version, the correct answer is either multiplied or divided by three or sometimes also a multiple of three so that the correct answer is not always the median number. The second version uses two or multiples of two and the third version uses 1.5 and multiples of 1.5. The levels of dif-

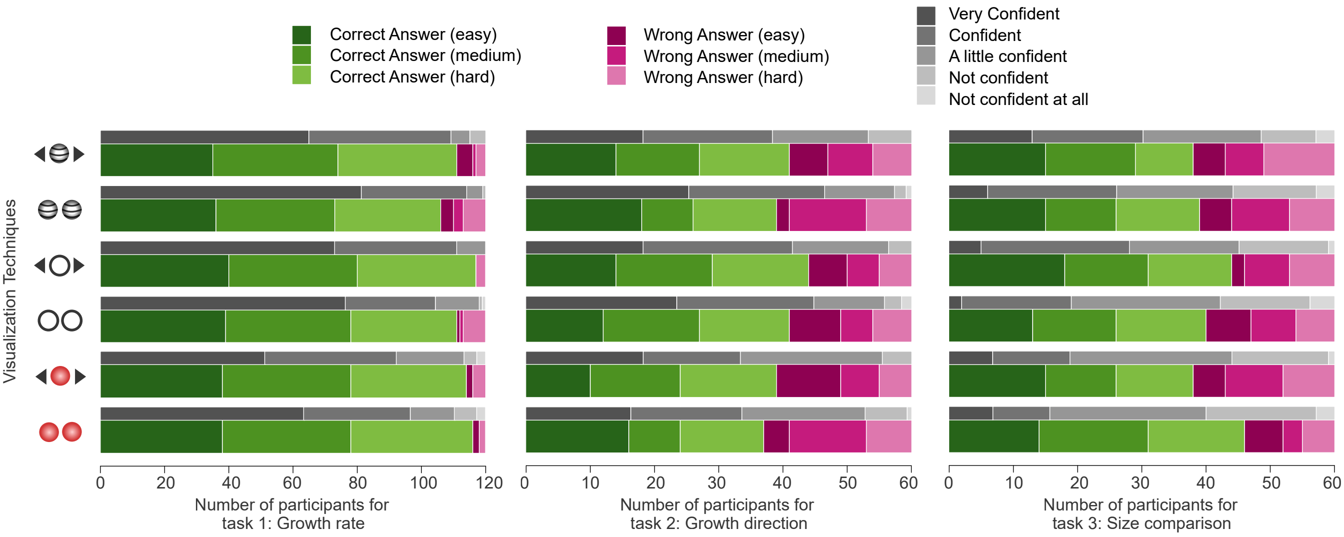


Figure 5: *Response options selected by participants, divided into three different levels of difficulty, paired with users' self-assessment of how confident they are in their responses. Each row shows the answers for one visualization technique, namely from bottom to top: Phong side-by-side, Phong successive, outline side-by-side, outline successive, Fresnel with hatching side-by-side, and Fresnel with hatching successive.*

ficulty of the answer options cannot be applied in this case, since we cannot say if it is harder to identify if a tumor has grown about the factor 1.5, two, or three.

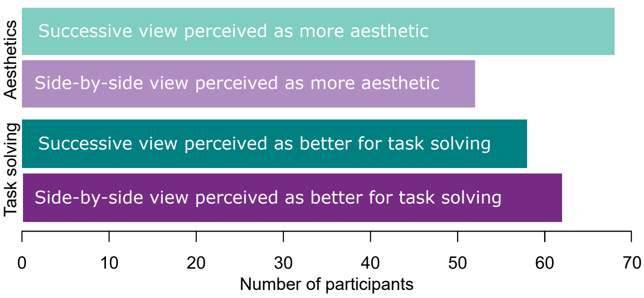


Figure 6: *Preferences indicated by the participants. For each of the two medical case studies, the participants were asked to indicate their preferred form of presentation for solving the tasks as well as from a purely aesthetic point of view. Therefore, each participant was asked twice about his or her preferences, resulting in a total of 120 responses for both task-solving and aesthetics.*

6. Discussion of Results

In the following, we discuss our results regarding the tasks, completion times, and preferences taking into consideration some study limitations.

6.1. Tasks

Participants had to solve three types of user tasks in a multiple-choice quiz, namely selecting the correct growth rate, growth direction, and size ratio from a set of three answer choices each. As described in Subsection 5.3, the first task, estimating the growth rate, is implemented for all data sets, while the other two tasks are implemented only for aneurysms or tumors. Thus, the first task received twice as many responses as the other two tasks.

Growth Rate. Estimating the growth rate over all data sets got fewer wrong answers, compared to the other two tasks, see Figure 5. The users who saw the hatching models displayed side-by-side got the fewest correct answers while the users presented with the outline model where time steps are shown successively got the best results. It is noticeable, that for the hatching visualizations, more wrong answers of an easy difficulty level were picked compared to the other visualization techniques. This might be caused by participants being confused due to the higher complexity of the visual scene caused by the hatching lines. Wrong answer options of the highest level of difficulty caused most of the wrong answers chosen by the participants overall for the task of estimating the growth rate. Confidence was lowest for the two versions using Phong shading, even though participants solved almost all of the questions correctly. Overall, however, the six visualization techniques show only minor differences in the evaluation results.

Participants argued that plateaus in the graph depicting the growth rate (see Figure 3 (a)) made the tasks rather easy, especially if the plateau was in the beginning. This is one possible explanation for why participants overall performed better in this task type than the others. Because the plateaus were placed in different positions for each answer choice, participants could identify the correct answer in many of the tasks simply by identifying the correct position of the plateau. Furthermore, the growth rate task could be solved without rotating the models. We noticed that many participants who took part in our evaluation at the *Long Night of Science* did not rotate the models. We assume that 3D interaction is not intuitive for people who are not familiar with virtual 3D spaces, e.g.

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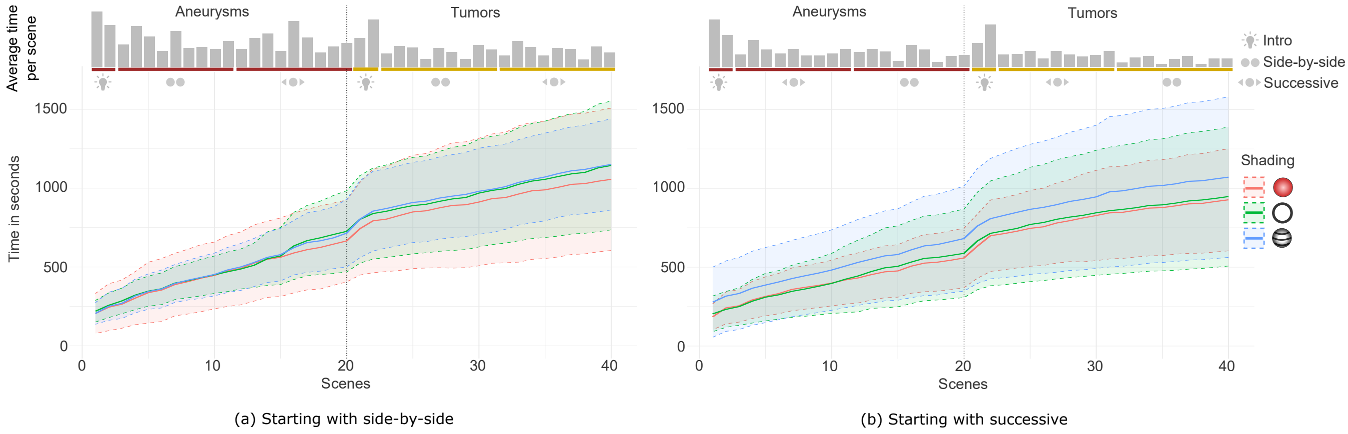

Figure 7: *The line graphs show study participant completion times (mean with standard deviation). (a) depicts the sequences where participants start with the side-by-side view. (b) shows the sequences that showed the successive view first. The colors represent the visualization techniques, namely Phong (red), outline (green), and Fresnel with hatching (blue). Above, a bar chart shows the average time participants spent in each scene. Colored lines depict if the scenes showed aneurysms (dark red) or tumors (yellow). Furthermore, icons indicate whether the scenes show an introduction, a side-by-side view, or a successive view.*

due to playing video games. Therefore, many users did not take advantage of the interaction opportunity even though it was explained at the beginning of the evaluation.

Growth Direction. For the tasks regarding growth direction, participants seeing the successive view performed better for all shading techniques. The most correct answers were given by users seeing the successive outline visualization. The confidence users had in their answers for the growth direction is higher for the successive view except for the versions with Phong shading. However, higher confidence does not correlate with a higher number of correct answers.

The overall number of incorrect answers is much higher for the estimation of the growth direction than for the growth rate. This is likely caused by many participants not using the option to rotate the models. Without rotating the object, the growth direction is hard to identify. We cannot see a clear trend regarding the level of difficulty of the wrong answer options as all levels were picked frequently by the participants.

Size Comparison. When comparing the size of two 3D models, the most correct answers were achieved by participants seeing the side-by-side view for the Phong shader, closely followed by the successive view for the outline shader. When comparing the results of the side-by-side view and the successive view for the same shaders, participants were able to identify more correct answers with the side-by-side views but had higher confidence in their answers when seeing the successive view. The only exception is the successive outline visualization which got more correct results than the side-by-side view. Estimating size ratios of 3D objects is generally a challenging task, which is heavily influenced by the objects' shape [KBK10]. Therefore, we expected participants to underperform in this task. This also explains the lower confidence participants had in their answers compared to the other two tasks. Nevertheless, the majority of the tasks were solved correctly.

Confidence was lowest for answer options scaled by a factor of 1.5, thus participants indeed perceived this variant as the most difficult. Answer options scaled by factor two got slightly lower confidence compared to answer options with scaling factor three. This matches the number of wrong answer options picked by the participants, where more false results were caused by answer options scaled by factors 1.5 and two.

General Remarks. The cases where outlines are used as visualization techniques and time steps are shown successively got the highest number of correct answers overall. It may be that participants were forced to use the rotation interaction due to limited depth perception when visualizing only outlines, leading to a higher number of correct responses regarding growth direction. However, participants seeing the side-by-side view of the outline visualizations performed worse. Thus, this effect cannot be explained by the outline shading alone but by the combination of the shading and the successive view. The visualization techniques that got the most correct answers per task varied. Thus, the representation format future visualizations should use is based on the communicative intent, e.g. it is beneficial to use a side-by-side view when the goal is to show size ratios to the users.

Interestingly, there were no significant differences observed between the six visualization techniques used in this study. Despite variations in shading and arrangement of the time steps, participants' performance did not vary substantially across these techniques. This suggests that the core aspects of the data itself, such as the complexity of the surface models, had a stronger influence on participants' performance than the specific rendering details. Examining participants' confidence levels in their answers, it was found that confidence did not always correlate with the number of correct answers. This suggests that participants might have lacked confidence in their judgments even when their responses were accurate. It is worth exploring whether this discrepancy arises from the visualization or other factors influencing participants' subjective confidence levels.

6.2. User Preferences

Users were asked to rate which type of presentation they preferred for the time steps regarding solving the tasks and aesthetically (see Figure 6). The preference regarding solving the tasks is almost equally distributed between showing all steps side-by-side and successively with a slight tendency for the former. However, more participants favored the successive display of time steps in terms of aesthetics. This means that some users who preferred a side-by-side view to solve tasks preferred the consecutive view in terms of visual appeal, leading to the awareness that user preferences for these aspects cannot always be reconciled. However, most users preferred the same visualization type for both aspects which matches the findings by Garrison et al. [GMF*21] that users generally prefer visualizations that match a stated communicative objective in their eyes.

6.3. Time Measurement

We measured the time the participants needed during our evaluation. The measurements per version were aggregated by calculating the mean as well as standard deviation (see Figure 7). For each shader, we can see that participants became slower for the first two scenes as well as scenes 20-22. In these scenes, the respective task is introduced.

Solving the tasks for the tumors took participants less time than the tasks for the aneurysms. This might be caused by a learning effect since the tumors were always shown in the second half of the evaluation. In addition, the tumors could be assessed more quickly at first glance, since they were depicted without neighboring anatomical structures. The aneurysms were always attached to a section of the vascular tree, which could have made the analysis more difficult.

The evaluation sequences do not show any major differences regarding the completion times. On average, users starting with the successive view first finished the evaluation slightly faster. The version that uses a Fresnel shader with additional hatching and starts with a successive view has overall slightly higher values compared to the other versions starting with a successive view. However, this is caused by one participant taking very long throughout the whole evaluation process. The familiarity of participants with computers and 3D interaction had a major influence on the time they needed. We also noticed that older participants tend to take more time to carefully consider all the information and to ask questions while younger participants tried to maximize the number of correct answers while minimizing the time they needed. Younger participants might also be more skilled in using a computer and 3D interaction.

6.4. Study Limitations

Due to the enormous size of the design space, we had to set limitations in our study. First, we decided to present discrete time steps to the participants. These were shown both simultaneously and successively. The user was able to steer the successive presentation of time steps using buttons. Alternative presentations of time steps are also possible, for example, an animation that switches between time steps automatically or to create the impression of continuous growth by morphing the 3D meshes when switching between time steps. By steering the sequential view of time steps, users are able to take as much time as they need and can go forward as well as backward. A self-playing animation would not adapt to the users' speed and only go forward. Therefore, it might be harder for users to solve the tasks with it. Therefore, and to limit the size of the design space, we chose to let the user steer the visualizations focusing on the question if users preferred to see all time steps at one glance or if that might be overwhelming and the concept of growth is more tangible when seeing the time steps successively.

Previous work on medical visualization of volume data provides a rich set of visualization techniques [PBC*16, LLPH15]. We have selected a small subset of three techniques some of which are also used in educational textbooks, e.g. illustrative techniques. The models we are using for the time steps are manually created. Only the last time step of each data set showing the full-grown pathology is derived from data. Therefore, the other time steps might not depict how the pathological structure evolved in reality. However, realism is not a major factor in this study. We compare different visualization techniques to communicate changes in the size of medical structures over time. Since the same models are used for every visualization technique, the results are comparable independent of the realism of the manually generated time steps.

We conducted a user study aimed at a general audience. Although we advertised our study to the general local population, the people who chose to participate tended to be young, highly educated, and many had prior knowledge of medical topics. As a result, the composition of our participant cohort does not reflect a representative cross-section of the broader population. However, because the same bias affects participants in all versions of the story, the results remain comparable.

6.5. Study Implications

Finding suited visualization techniques does not only depend on the medical scenario (e.g., pathological growth) but also on the communicative intent. For example, showing multiple time steps side-by-side facilitates the perception of size ratios more effectively, while a successive visualization of the time steps supported the participants better when estimating growth rate and direction. Thus, users should be able to switch between multiple visualization techniques, perhaps with some guidance on which visualization technique to choose for which aspect of the data. However, the offered visualization techniques must be selected carefully. Additional visual aids do not necessarily support users in analyzing the data. On the contrary, it might even impair a user's ability to analyze the data by increasing the visual complexity of a scene. Even though combining the Fresnel shader with hatching lines offered more visual aids to the users, the results of the multiple-choice tasks were generally worse compared to the other visualization techniques. Therefore, our study implies that simplicity is desirable for visually communicating medical image data to a general audience. This is also consistent with the observation that participants were able to solve the tasks faster when viewing the tumor only compared to when viewing the aneurysm with the attached vascular tree, where the latter introduced anatomical context but at the same time increased visual complexity.

We are able to see that many users tend to be *"lazy"*, meaning that they do not use interaction possibilities if they do not deem them necessary. For the participants from the in-person event, we saw that only a few tend to regularly rotate the objects and the ones who did were generally younger. We noticed that oral explanations, textual hints, and icons are not sufficient to motivate users to use interaction techniques throughout multiple scenes. After leaving the introductory scene, where the interaction possibilities are introduced, many participants did not use them anymore. Using the design of our visualizations, we might be able to steer if we want users to interact (e.g., due to the limited depth perception when using an outline shader, rotation becomes more important to generate a parallax effect as an additional depth cue) or if we want to design visualizations where interaction is redundant. Forcing users to interact in order to understand the visually conveyed message can lead to frustration if they do not master the interaction techniques offered. On the other hand, it can be a way to more efficiently introduce an audience to 3D interaction techniques.

7. Conclusion and Future Work

Our user study showed that the participants performed rather similarly in the user tasks, regardless of the visualization technique they were presented with. We asked about users' preferences regarding the side-by-side view as well as the successive view. Future studies should also investigate user preferences regarding the different visualization techniques, in our case Phong, outline, and Fresnel with hatching. Since aesthetics is an important aspect of visual communication, this would shed more light on which visualization technique should be implemented in data-driven stories.

Aneurysms as well as tumors can create bulges, so-called blebs. For aneurysms, these blebs are often associated with an increased risk of rupture while an irregular shape indicates that a tumor is malignant. Therefore, blebs are critical in assessing the pathology. Future studies should investigate how to convey not only the change in size but also the change in shape over time. In addition, a number of other shading techniques can also be evaluated as part of such a study. For implementing user studies investigating how to communicate morphological changes of pathologies, realism is more important than for investigating the perception of size differences. Therefore, consultations with clinicians are needed to ensure artificially generated time steps meet a certain level of realism. Additionally, mathematical growth models can be used to generate realistic time steps of pathological changes [SSB21, PTZ21, AKA*20]. On the other hand, further studies could investigate the influence of surface complexity on the difficulty of certain tasks. Therefore, anatomical structures could be further abstracted, e.g. using spheres.

Our study investigated static, discrete time steps for non-periodic time-oriented medical image data. However, temporal changes can also be shown using animations. Therefore, future research is needed to investigate if animations can support users in understanding and analyzing growth processes. Additionally, future studies can build upon our work to investigate how to visually communicate periodic medical data, such as pulsating blood flow or a beating heart.

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