EDITOR: Theresa-Marie Rhyne, theresamarierhyne@gmail.com

DEPARTMENT: VISUALIZATION VIEWPOINTS

Ten Open Challenges in Medical Visualization

Christina Gillmann, *Leipzig University, 04109, Leipzig, Germany*

Noeska N. Smit, *University of Bergen and Haukeland University Hospital, 5007, Bergen, Norway*

Eduard Gröller, *TU Wien and VRVis Research Center, 1220, Wien, Austria*

Bernhard Preim, *University of Magdeburg, 39106, Magdeburg, Germany*

Anna Vilanova, *Eindhoven University of Technology, AZ 5612, Eindhoven, The Netherlands*

Thomas Wischgoll, *Wright State University, Dayton, OH, 45435, USA*

The medical domain has been an inspiring application area in visualization research for many years already, but many open challenges remain. The driving forces of medical visualization research have been strengthened by novel developments, for example, in deep learning, the advent of affordable VR technology, and the need to provide medical visualizations for broader audiences. At IEEE VIS 2020, we hosted an Application Spotlight session to highlight recent medical visualization research topics. With this article, we provide the visualization community with ten such open challenges, primarily focused on challenges related to the visualization of medical imaging data. We first describe the unique nature of medical data in terms of data preparation, access, and standardization. Subsequently, we cover open visualization research challenges related to uncertainty, multimodal and multiscale approaches, and evaluation. Finally, we emphasize challenges related to users focusing on explainable AI, immersive visualization, P4 medicine, and narrative visualization.

Medical visualization has a long tradition ranging from anatomical drawings by Vesalius to the discovery of the X-ray in 1895 and the resulting ability to examine structures inside the human body in a noninvasive manner. Since then, medical visualization has developed into a standard tool to aid diagnosis, plan treatment options, and monitor the health of patients. In addition, diversity in treatment opportunities has increased as well. For example, in tumor treatment, immunotherapy and surgery can now be better tailored to individual patients and combined for optimal outcomes. The increasing diversity of treatment opportunities also leads to an increased need for decision making, which can be supported with appropriate visualization techniques. Driven by continued advances in the medical field, such as novel imaging technologies and increased image quality, digitization, and complexity, medical visualization is still an in-demand scientific discipline that is directly driven by medical applications. The visualization of medical data has led to many technical advances in the field of visualization, for example, volume rendering as early as 1986.[a] Medical datasets are commonly used to benchmark novel visualization

Christina Gillmann and Noeska N. Smit are joint first authors and contributed equally to this work.

0272-1716 © 2021 IEEE
Digital Object Identifier 10.1109/MCG.2021.3094858
Date of current version 8 September 2021.

[a]https://medvis.org/2012/01/30/hohne/

techniques, as these provide nontrivial and real-world datasets that can be used as a gold standard for testing. Computational developments in machine learning and the advent of affordable virtual reality technology lead to additional medical visualization research opportunities. While the medical domain has been an important application area for application-driven research in visualization for many years, further research is still needed. In addition to publications and sessions at our top visualization venues, the dedicated Visual Computing in Biology and Medicine and Visual Analytics in Healthcare workshop series demonstrate continued research interest in the field.

An increasing number of challenges arising from the medical field combined with computational advances lead to opportunities to develop novel analysis and visualization approaches. In 2012, Botha *et al.*[1] summarized open challenges in medical visualization, focusing in particular on scaling medical visualization from one[1] to many. In 2015, IEEE VIS featured a tutorial on Rejuvenated Medical Visualization, where visualization of large-scale data, whole-body data, physiology data, nonstandard imaging and simulations, and cohort studies were identified as promising research areas for the future. Since then, some challenges have received attention, while others were neglected. Some challenges have evolved by new developments in the medical domain. In addition, new challenges arose from rapid developments in computer science, such as the increasing role of Artificial Intelligence (AI) technologies for medical image analysis.

This article outlines ten open challenges in medical visualization from different perspectives. It is based on discussions in our Application Spotlight and an informal survey among 14 participants from a wide range of backgrounds from academia and industry. Our focus in this article is on challenges centered around the visualization of structured medical data, e.g., medical imaging data. While some challenges are more practical in nature, relating to barriers encountered when working with medical data, others relate to more fundamental open visualization research questions. We begin by outlining several practical challenges related to the visualization of medical data, in terms of data preparation, access, and standardization. Subsequently, we discuss core visualization research challenges in the medical domain related to uncertainty, multimodal and multiscale visualization, and visualization evaluation challenges. Finally, we discuss challenges arising from targeting specific user groups: explainable AI, immersive visualization, P4 medicine, and narrative visualization. Our aim in highlighting these challenges is to provide an overview and to guide further medical visualization research. This article is intended to inform early-career visualization researchers and to provide an overview of exciting open avenues in medical visualization research.

DATA-SPECIFIC CHALLENGES

Medical visualization research is partially driven by the development of novel techniques in the medical domain itself. For example, novel scanners are developed, which provide new types of imaging modalities presenting unique visualization challenges. There is a wide range of different data types available in a medical context, e.g., data from medical imaging scanners, sensors, or patient metadata. Even when just considering a single scanner, different types of data can be obtained resulting in single scalar, tensor, and vector fields, as well as multivalued data. Part of the challenge in medical data analysis is that these data can be messy, noisy, heterogeneous, and/or hard to interpret. This could be due to noise inherently present in the data, different confounding effects such as patient movement and keeping X-ray dose low or lack of consistency in metadata recording, for example. In the following, we discuss practical medical visualization challenges arising from the nature of medical data.

Data Preparation

Before medical data can be visualized, the raw data needs to be processed in most cases. This can include several techniques such as image enhancement, segmentation, or data transformation. Each of these is research topics in and of themselves, and it can be hard to determine the proper processing techniques or, if required, an entire pipeline of techniques. The choice of data preparation techniques dramatically influences the quality of the resulting visualization. Here, a collection of unified pipelines or workflows for data preparation is still an open problem. In image analysis, custom solutions are needed for segmentation depending on the imaging modality and anatomical region. In visualization, we often have general solutions, e.g., for visualizing vascular structures, no matter where they occur in the body. Image analysis has to cope with the specifics of the anatomical region, biological diversity, and diversity of scan parameters. The latter may in principle be more standardized to reduce the problem slightly. To solve this issue, collaborations with researchers from image processing disciplines are required. In addition, developing a taxonomy of medical tasks could lead to an improved understanding and better generalizability of application-oriented medical visualization research. While we are not aware of any ongoing initiatives, this would be a highly valuable addition to the visualization literature.

Extracting Features

Medical data are diverse and usually captures a variety of aspects. This relates to medical records that are written by clinicians and ranging from sensor data to medical image data that captures multiple organs. When considering medical imaging data, features of interest could be the locations of anatomical landmarks, centerlines of elongated structures, the orientation of diffusion fibers, or geometric descriptors. Such features are increasingly extracted by deep learning techniques. However, medical knowledge is needed to label imaging data in order to train deep learning networks. There exists a variety of approaches to automatically extract features from data, especially in medical image segmentation, but unfortunately, such methods often do not work out of the box. In particular, most machine learning techniques reproduce human behavior or are biased toward the datasets trained on. As such, black box solutions do not work. Especially in the medical domain, decisions that affect patient lives need to be made carefully. Thus, a fully automated extraction of meaning from medical data are not possible. Instead, visualization approaches that show the original data in relation to the predicted outcome for decision support are more appropriate. The final decision-making is done by experts who need to understand why a system offers a certain suggestion. Automatic methods are based on datasets and assumptions that are not always valid. Therefore, it is important to be able to explain and communicate adequately, an area in which visualization can play a major role.

Data Assimilation

In data assimilation,[2] measured data are combined with computational models. The idea is to couple observed data and the underlying dynamical principles governing the system. In this way, an estimate can be provided that is better than what could be obtained using either measured data or models alone. This principle arose from environmental sciences, where the aim was to enhance climate models and predictions.

De Hoon *et al.*[3] applied this principle to blood flow, combining measurements and computational models (see Figure 1). The potential offered by data assimilation is not frequently explored in medical visualization, however. Especially in recent years, where more and more computational models are utilized, data assimilation becomes an important challenge. While data assimilation as a field has a long history, for visualization, there is an additional challenge to keep computation times low to allow for interactive exploration.

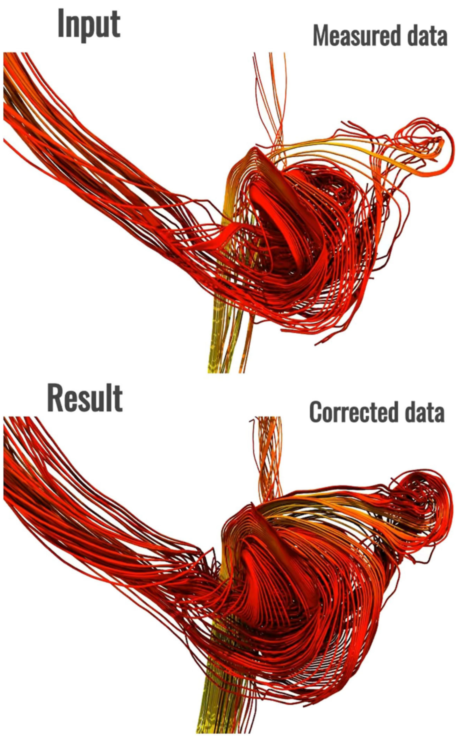

FIGURE 1. In data assimilation, measurements and computational models are combined to improve precision, in this case to gain insight into blood flow patterns. Flow features are preserved while more streamlines are visible due to reduced divergence and flow outside of the segmentation.[3]

Data Access

In addition to data preparation practicalities, gaining access to appropriate data may be challenging due to availability or ethical consideration around the use of such data.

Data Curation

Data curation[4] refers to the organization and integration of data collected from various sources. Lack of curation results in a significant amount of work that needs to be repeated every time new visualization research is performed. A curated database of datasets and visualization approaches would be of great benefit for visualization re searchers. We could be inspired by the protein data bank (PDB)[b] as used in molecular modeling. While several initiatives exist, e.g., the Cancer Imaging Archive,[c] a unified platform is lacking,

[b]https://www.rcsb.org/
[c]https://www.cancerimagingarchive.net/

likely due to the sensitive nature of medical data and lack of standardization.

Publicly Available Data

Publicly available datasets play an important role in the development of novel visualization techniques. These datasets are required to test prototypes of medical visualization approaches and identify potential avenues for improvement. In contrast to other disciplines, medical data can usually not be made public easily. Laws demand that any shared data needs to be made anonymous and in many cases, patient consent is required. In addition, regulations at times stipulate that data shared within larger projects may only be used only within the context of the project. While phantom data are not associated with specific patients, even this is not often made freely available. This results in a scarcity of freely available datasets to advance developments in the field of medical visualization. Moreover, it leads to an undesirable scenario in which only those in close collaboration with medical partners may have such data available. In medical image analysis, often datasets are provided through grand challenges. These challenges allow for an effective benchmarking of novel techniques by enabling performance comparisons on the same data. Medical visualization would also benefit from such benchmark datasets. This would be in line with best practices to promote open science and could increase reproducibility. A reasonable first step toward this might be to make a set of vascular surface models freely available, e.g., coronary, peripheral, and abdominal vessels. As a second step, such models could be enriched with results from blood flow simulation or measurements.

Ethical Considerations Around Data Usage

Independent of the application area, ethical issues are an increasingly relevant topic in computer science. In particular, such issues play a large role when considering machine learning approaches trained on personal data and disease risk information originating from genome analysis. In many applications, it is not clear if data are cleared for specific use cases and who needs to give permission to do so. The legal frame surrounding this topic needs close consideration. Ensuring that medical visualization research was conducted in an ethical manner will likely become more prominent in the upcoming years. Such ethical considerations also play a big role in data privacy regulations.

Data are usually owned by a person or an institution. This ownership implies rights that need to be considered when aiming to use data sources for research and publication. Unfortunately, no general regulation (not even at a country level) exists that clarifies what type of data can be used and in which sense. In addition, even if a patient or institution allows the use of specific data sources, the question arises which analysis results are cleared for publication. This can result in difficulties in accessing important data sources when developing novel visualization approaches. While this is a general challenge for anyone working with data, clinical data falls under the special personal data category in EU law under the General Data Protection Regulation (GDPR), also referred to as sensitive personal data. This imposes strict limitations on how such data can be used. Thorough anonymization may alleviate some concerns, but is challenging for certain data types. For example, a CT scan of the head can easily be made recognizable through volume rendering.

Standardization

There are already a significant number of well-established standards in the medical domain, such as the Digital Imaging and Communications in Medicine (DICOM) standard and standards for different measures, such as tumor staging criteria. However, such standards do not exist for visualization. For all advanced imaging techniques, standardization and harmonization are a serious problem. For special acquisition methods, e.g., perfusion or spectroscopy, the results do not only depend on the patient. To a strong extent, these rather depend on the particular device, sequences, and protocols, which are all vendor-specific. Missing standardization is a large issue that prevents the widespread use of these advanced modalities and the transformation of research prototypes into products. Standardization is even a challenge in large-scale health surveys. Although acquisitions are as similar as possible, there are noticeable differences. This leads to a challenging situation for visualization researchers who are looking for broader applicability of their visualization techniques and tools.

Guidelines on how to interpret the data are difficult to establish when results are so different between multiple devices. The Surgical Data Science[d] initiative also discusses the challenge of lacking standardization frequently.

VISUALIZATION CHALLENGES

In addition to practical challenges arising from the specific type of data dealt with in medical visualization,

[d]http://www.surgical-data-science.org/

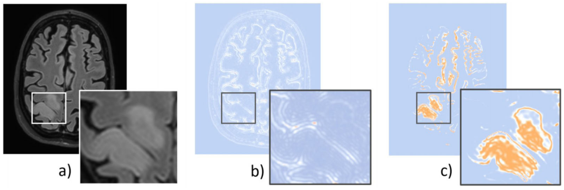

FIGURE 2. Visualization of uncertainty continues to be an important challenge. Shown here is uncertainty-aware visualization for brain lesions with (a) an original MRI, (b) noise estimation, and (c) entropy estimation.[5]

there are challenges that we consider core medical visualization research challenges. Some challenges have been extensively commented on in previous work, for example, moving from the visualization of individuals to population data.[1] In the following, we outline three additional open visualization challenges.

Uncertainty Visualization

In particular in medicine, where large amounts of data are acquired in order to determine optimal treatment strategies, the communication of uncertainty is an important factor to ensure appropriate treatment decisions. It is paramount to make physicians aware of the uncertainty resulting from working with measured data and which visualized parts of the data warrant additional investigation. It is not always the case that clinicians are eager to see this uncertainty, as it may be considered confusing or problematic. Especially in these cases, it is a challenge to design appropriate visual encodings to break these barriers. For modalities where the analysis is performed on derived entities from the measurements, such as Phase Contrast Magnetic Resonance Imaging (PC-MRI) or Diffusion-weighted imaging (DWI), this becomes even more critical as the raw images are not suitable for exploration and identification of the possible areas and sources of uncertainty.

Many types of data are usually messy and represent large and complex anatomic or metabolic systems. Uncertainties arise in different manners when visualizing medical imaging data. These uncertainties strongly influence the decision-making process of clinicians. There exists a variety of uncertainty quantification and visualization approaches, such as heatmaps (see Figure 2), but appropriate approaches need to be selected and tailored to specific use cases. This includes three major steps: uncertainty modeling, uncertainty propagation, and uncertainty visualization. A general overview of the state of the art in uncertainty visualization in medical imaging is available in the survey by Gillmann *et al.*[6]

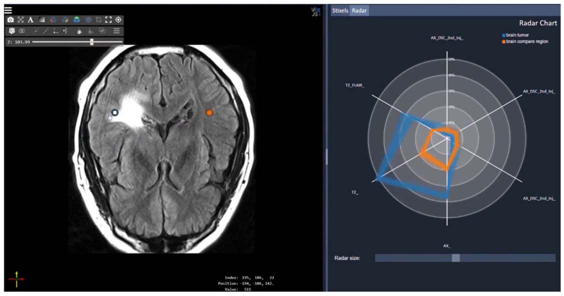

FIGURE 3. The exploration and analysis of multiple imaging modalities simultaneously requires an integrated view. In this figure, ParaGlyder allows for multiparametric brain imaging exploration to explore multiple datasets simultaneously.[8]

Multimodal and Multiscale Visualization

Multimodal data acquisition occurs often in the medical context, as its complementary information leads to improved diagnosis or treatment. In addition to data from multiple scanners, single scanners can also offer a variety of contrasts. Exploring complementary modalities simultaneously allows for a more detailed pathology and healthy tissue characterization (see Figure 3). Lawonn *et al.*[7] identified open challenges for this area in a state-of-the-art report on multimodal imaging data visualization. Uncertainty in the registration process, lack of thorough evaluations, lack of ready-to-use software, and visualization of more than two modalities were identified as open challenges. Focus-and-context depictions, illustrative visualization, ghosted views, and cut-aways were identified as key visualization techniques to identify what is the essential information to reveal from which modality. In addition to multimodal medical imaging data, heterogeneous data analysis is challenging. Combining data from multiple sources effectively provides further challenges to those already originating from combining multiple imaging modalities. While some preliminary work in this area has been done, this could be further extended to focus on time-varying or cohort data analysis. As the complexity and amount of data increases, a combination of computational and visual approaches is needed, often referred to as visual data science.

Medical imaging can be done at a variety of scales, from histopathology to whole-body MR scans. Multiscale data refer to data that captures the same physical behavior but on different size scales. Currently, in clinical practice, different scales are usually not analyzed simultaneously if the difference in scale is too large. As more imaging techniques are developed which bridge scales, the main challenge will be to find suitable links between the different scales and visual representations as well as interaction techniques that can integrate these effectively. This is closely related to multimodal data analysis, as the datasets usually need to be registered in order to be visualized simultaneously. In addition, the different scales need to be expressed in the visualization. Here, focus-and-context approaches are required. Interaction via zooming and filtering further are ways to present the information at different scales effectively. Furthermore, data on different scales usually are given in different resolutions that need to be expressed in the visualization.

Visualization and Data Processing Evaluation

Independent of the application domain, novel visualization approaches need to be compared to existing approaches. There can be a variety of tests including performance, user acceptance, efficiency, and effectiveness tests. Performance measures in terms of speed and storage consumption exist, but evaluating characteristics such as effectiveness is a challenge. A major problem here is the need for expert users, whose number is usually very limited, and the difficulty of showing that visualization has real added value for the clinical decision-making and outcome. Due to the limited availability of domain experts, large user studies suitable for statistical analysis are out of the question for most applications. This leads to evidence that often does not go beyond anecdotal, in turn leading to hindered acceptance. As such, suitable metrics for medical visualization evaluation[9] need to be defined. Medical visualization researchers could be inspired further by performance measures beyond correctness and time, as frequently discussed at the BELIV workshop.

USER-SPECIFIC CHALLENGES

New challenges arise when targeting specific user groups with medical visualization. Different visualization techniques are needed to address specific audiences to support various tasks. For example, a visualization supporting clinicians might be different than one aimed at supporting education. The following four visualization challenges arise from targeting different audiences.

Explainable AI

Despite the success of artificial intelligence-based methods, a common barrier to acceptance in a clinical context is the black-box nature of such methods. This also limits the possibilities of model improvement and the generation of new knowledge. Visualization and visual analytics can play a key role in establishing methods for explainable AI (XAI)[10] in order to open this black box.

There are multiple efforts in the visualization community to provide XAI solutions. However, the problems are often not easy to generalize and are application-, user-, data-, and model-dependent. Visualization provides a way to compare predicted and actual progress. It identifies important areas in the image that led to the prediction. This is an important mechanism to provide insight to the clinicians into employed machine learning approaches. In general, questions that end users may wish to answer are: Why was this decision recommended? What features contribute the most to this recommendation? How certain is the model that this is the right recommendation? Improved interpretability is needed for multiple reasons, for example, for diagnosis, evaluating model performance, understanding, and refinement. In addition, data provenance may heighten transparency and trust. Under the GDPR, people have a right to an explanation of all decisions made by automated or artificial intelligence algorithms.[e] An open challenge here is that this is not a well-defined problem and it is unclear what constitutes a good explanation. Visualization can learn from other disciplines, such as from pedagogical and psychological sciences to learn what good explanation and understanding constitute.[11]

Immersive Visualization

While display technologies such as virtual reality (VR) and augmented reality (AR) have been around for decades, their application to the medical domain still offers many challenges. These technologies have been met with great excitement in the past with several phases in which technological advancements have made the techniques more viable. The latest round of technological improvements involved higher resolution displays at significantly lower cost, making these devices more accessible to a greater group of people.

A potential benefit of VR and AR in the medical domain is the improved immersion, which enables a good understanding of complex spatial relations. In addition, the increase in realism of simulations and visualizations can benefit the medical domain. Particularly educational applications are shown to be effective using augmented and virtual reality. Augmented

[e]https://gdpr-info.eu/recitals/no-71/

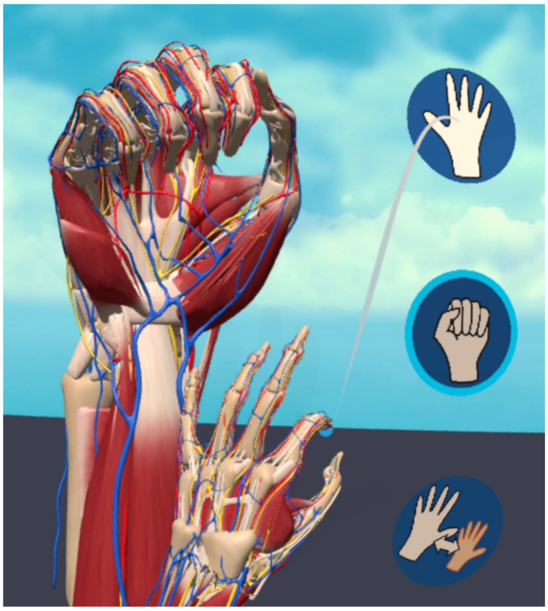

FIGURE 4. Immersive visualization offers many opportunities to explore complex medical data. In the educational tool pictured, users can explore anatomy of the hand in VR via live tracking of the user's hand in comparison to a bigger anatomical model.[12]

reality techniques can be used to visualize additional data by superimposing supplementary information onto a patient's body. There are potentially a lot of applications for these technologies, such as surgical guidance or training. Further research is necessary to identify the most effective approaches and applications for VR and AR in medical visualization.

One area in which immersive visualization is a very promising approach is medical education, for example, to learn human anatomy.[13] Saalfeld *et al.*[12] (see Figure 4) used a virtual reality environment to educate medical students about the anatomy of the hand by projecting anatomical details onto the user's hand and offering the option to explore a larger model. Here, open challenges are integrating more modalities than 3-D visualization, further exploration of the use and benefits of VR, and providing adaptive visualizations tailored to the learner.

Beyond Diagnosis and Treatment

In early medical visualization research, much of the focus was on visualizing anatomy from a single scan. This only provides a snapshot of a patient's current health status, which can be suitable to aid diagnosis or treatment planning. However, in order to target P4 medicine (Predictive, Preventive, Personalized, and Participatory), i.e., beyond diagnosis and treatment planning, more integrated and comprehensive analysis methods are needed. For example, prediction may be achieved by integrating automatic approaches with explainable AI support and uncertainty visualization. In order to aim at prevention, visualization methods for public health data can play a key role in improving the overall health of the population, which is an area where there are still many open visualization challenges.[14] Personalization of treatment may be achieved by integrating radiologic and genomic features in a multimodal visualization approach to research the tailored treatment opportunities. To increase patient participation, more work could be done to facilitate effective personalized doctor–patient communication methods such that patients can make informed decisions on treatment options, for example, through physicalization. Rather than relying on generic illustrations to explain a disease or procedure, a patient could be shown his or her own data in order to provide a personalized view of the situation.

Narrative Visualization

Narrative visualization, aiming at communicating scientific results to broad audiences, experiences a lot of attention in various application areas. Merging exploratory and explanatory visualization could effectively support knowledge acquisition for nonexperts regarding many scientific processes. Medical research results, e.g., mechanisms that explain pathological processes, avoidable risk factors for diseases, or just mechanisms of the healthy human body are also interesting for broad audiences. Medical knowledge is immediately relevant for patients and their relatives but also athletes and other groups benefit from medical knowledge. Narrative medical visualization based on actual measured data (data-driven) or based on artificial geometric models is an essential challenge for the future. The effective design of interactive animations, the interactive abstraction of medical surface models, and effective strategies to integrate labels, textual explanations or metagraphic symbols, such as arrows are specific tasks to be tackled in this context. Medical visualization could be inspired by a rich body of literature on storytelling in visualization.[15]

DISCUSSION

The medical application domain continues to provide an inspiring environment with many research opportunities. Medical visualization applications cannot be developed without maintaining a close collaboration with medical experts. In addition, to translate research to practice, collaboration with industry is needed. In contrast to many other application domains, clinical daily routine imposes an additional set of restrictions, such as limited access to high-end hardware and the need for certification for clinical use.

In practice, medical visualization research often targets medical researchers rather than clinicians. A benefit here is that medical researchers have more time available to help develop and evaluate techniques. In this case, the visualization technique needs to add value over existing tools before medical researchers consider adopting novel techniques.

Given the ten challenges outlined, a question arises if these can be prioritized, or if there are order dependencies between them. We found no such prioritization possible and noted that many of the challenges are closely interlinked and approaches can cover aspects of a variety of challenges. In addition, while medical visualization can target a single challenge, from the user's perspective this might not completely solve their problem. It could be that image processing and simulation need to be combined with visualization for a complete solution.

At a recent Shonan Meeting on "Formalizing Biological and Medical Visualization," further open challenges were discussed and we refer interested readers to the report for further discussion of key issues in biomedical visualization.[f] As in other applied visualization fields, medical visualization also has difficulty in developing unified medical visualization software frameworks. While Ph.D. candidates often develop prototypes to accompany research papers, the development of a larger unified framework is challenged by difficulties in attracting funding for pure software development efforts. A unified framework that includes existing solutions and can be extended if novel visualization approaches are developed would be a valuable resource. Such visualization software development challenges were recently discussed at a Shonan Meeting and we refer interested readers to their report to learn more.[g] This discussion will continue in an upcoming Shonan Meeting.[h]

While we have focused primarily on visualization challenges related to structured medical imaging data visualization, additional research opportunities await in the visualization of nonstructured medical data. Here, techniques such as progressive visual analytics and visualization provenance can contribute to addressing challenges in this area. In addition, truly integrated approaches targeting heterogeneous biomedical data visualization are so far underexplored. Neighboring disciplines such as biological data visualization are thoroughly developed, especially in genetic and molecular visualization, but bridges to the medical domain are still lacking.

[f]https://shonan.nii.ac.jp/seminars/167/
[g]https://shonan.nii.ac.jp/seminars/145/
[h]https://shonan.nii.ac.jp/seminars/193/

CONCLUSION

In this opinion piece, we outline ten major open challenges in the visualization of medical data. While some are of a practical nature, such as those surrounding data availability and preparation, there are still many open areas of visualization research. We highlight several avenues to potentially address these challenges and selected contributions in these areas. This manuscript is intended to function as a starting point for researchers in medical visualization to understand the open problems in this field, in particular focusing on medical imaging data. It is our hope that these ten challenges provide some directions to a fruitful research path and inspire further discussion.

ACKNOWLEDGMENTS

The authors would like to thank all participants in the informal ad hoc opinion poll and the attendees of the IEEE VIS Application Spotlight "Recent Challenges in Medical Visualization" for their valuable input and the fruitful discussion that led to this work. In particular, the authors acknowledge the feedback of the following colleagues: Wolfgang Birkfellner, Marcel Breeuwer, Katja Bühler, Dominik Fleischmann, Florian Ganglberger, Bernhard Kainz, Gabriel Mistelbauer, Christian Nasel, Renata Raidou, Rüdiger Schernthaner, Gerald Schröcker, Maurice Termeer, Rainer Wegenkittl, and Wolfgang Weninger. Part of this work was enabled by the Trond Mohn Foundation (811255) and VRVis is funded in COMET (879730), a program managed by FFG.

REFERENCES

1. C. P. Botha, B. Preim, A. E. Kaufman, S. Takahashi, and A. Ynnerman, *From Individual to Population: Challenges in Medical Visualization*. London, U.K.: Springer, 2014, pp. 265–282.

2. Z. Zhang and J. C. Moore, "Chapter 9—data assimilation," in *Mathematical and Physical Fundamentals of Climate Change*, Z. Zhang and J. C. Moore, Eds., Boston, MA, USA: Elsevier, 2015, pp. 291–311.
3. N. H. L. C. de Hoon, A. Jalba, E. Farag, P. van Ooij, A. Nederveen, E. Eisemann, and A. Vilanova, "Data assimilation for full 4D PC-MRI measurements: Physics-based denoising and interpolation," *Comput. Graph. Forum*, vol. 39, no. 6, pp. 496–512, 2020.
4. F. A. Satti, T. Ali, J. Hussain, W. A. Khan, A. M. Khattak, and S. Lee, "Ubiquitous health profile (UHPr): A big data curation platform for supporting health data interoperability," *Computing*, vol. 102, no. 11, pp. 2409–2444, 2020.
5. C. Gillmann *et al.*, "Uncertainty-aware brain lesion visualization," in *Proc. Eurograph. Workshop Vis. Comput. Biol. Med.*, 2020.
6. C. Gillmann, D. Saur, T. Wischgoll, and G. Scheuermann, "Uncertainty-aware visualization in medical imaging—A survey," *Comput. Graph. Forum*, vol. 40, pp. 665–689, 2021.
7. K. Lawonn, N. Smit, K. Buhler, and B. Preim, "A survey on multimodal medical data visualization," *Comput. Graph. Forum*, vol. 37, no. 1, pp. 413–438, 2018.
8. E. Mörth, I. S. Haldorsen, S. Bruckner, and N. N. Smit, "ParaGlyder: Probe-driven interactive visual analysis for multiparametric medical imaging data," in *Proc. Adv. Comput. Graph.*, 2020, pp. 351–363.
9. B. Preim, T. Ropinski, and P. Isenberg, "A critical analysis of the evaluation practice in medical visualization," in *Proc. Eurograph. Workshop Vis. Comput. Biol. Med.*, 2018, pp. 45–56.
10. E. Tjoa and C. Guan, "A survey on explainable artificial intelligence (XAI): Towards medical XAI," *IEEE Trans. Neural Netw. Learn. Syst.*, pp. 1–21, 2020.
11. F. C. Keil, "Explanation and understanding," *Annu. Rev. Psychol.*, vol. 57, pp. 227–254, 2006.
12. P. Saalfeld, A. Albrecht, W. D'Hanis, H.-J. Rothkotter, and B. Preim, "Learning hand anatomy with sense of embodiment," in *Proc. Eurograph. Workshop Vis. Comput. Biol. Med.*, 2020.
13. B. Preim and P. Saalfeld, "A survey of virtual human anatomy education systems," *Comput. Graph.*, vol. 71, pp. 132–153, 2018.
14. B. Preim and K. Lawonn, "A survey of visual analytics for public health," *Comput. Graph. Forum*, vol. 39, no. 1, pp. 543–580, 2020.
15. E. Segel and J. Heer, "Narrative visualization: Telling stories with data," *IEEE Trans. Vis. Comput. Graphics*, vol. 16, no. 6, pp. 1139–1148, Nov./Dec. 2010.

CHRISTINA GILLMANN is a Researcher of the Signal and Image Processing Group with the University of Leipzig. She is working in the area of image processing, especially under the aspect of uncertainty. She is the corresponding author of this article. Contact her at gillmann@informatik.uni- leipzig.de.

NOESKA N. SMIT is an Associate Professor in medical visualization at the University of Bergen, and at the Mohn Medical Imaging and Visualization Centre in Norway. Her research interests include developing novel interactive visualization approaches for multimodal medical imaging data. Contact her at noeska.smit@uib.no.

EDUARD GRÖLLER is a Professor at TU Wien, where he is heading the Research Unit of Computer Graphics. He is a key researcher of the VRVis research center. He is an adjunct professor of computer science at the University of Bergen, Norway. His research interests include computer graphics, visualization, and visual computing. Contact him at groeller@cg.tuwien.ac.at.

BERNHARD PREIM is a Professor of visualization at the Otto-von-Guericke University of Magdeburg. His research interests include visualization, visual analytics, and virtual reality in medicine with a focus on medical education, diagnosis of vascular diseases, and tumor surgery planning. Together with Charl Botha, he initiated the VCBM workshop series and led the steering committee of that workshop from 2013 to 2019. Contact him at bernhard@isg.cs.uni-magdeburg.de.

ANNA VILANOVA is a Professor of visual analytics with the Eindhoven University of Technology, The Netherlands. Her research interests include medical visualization for diffusion-weighted imaging and 4-D flow, visual analytics, uncertainty visualization, explainable AI, and multivalued visualization. Contact her at a.vilanova@tue.nl.

THOMAS WISCHGOLL is a Professor and the NCR Endowed Chair at Wright State University. He is also the Director of data science at Wright State. His research interests include scientific visualization, flow visualization, virtual environments, augmented reality, and display technology, as well as biomedical imaging and visualization. Contact him at thomas.wischgoll@wright.edu.

Contact department editor Theresa-Marie Rhyne at theresamarierhyne@gmail.com.