Open Challenges in Medical Visualization

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***Abstract*—While the number of publications in the medical field constantly increases, medical visualization publications do not necessarily follow the same trend. As developments in the medical domain are the driving force of medical visualization research, there are still many open challenges for medical visualization researchers. This is currently not reflected in the number of publications on this topic at our premier publication venues. At IEEE VIS 2020, we hosted an Application Spotlight session to highlight such open challenges. With this article, we hope to inspire the visualization community by providing an overview of open challenges and setting a research agenda for the future of medical visualization.**

INTRODUCTION

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 non-invasive manner. Since then, medical visualization has developed into a standard tool to aid diagnosis, plan treatment options, and monitor the health of patients. 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 dis-

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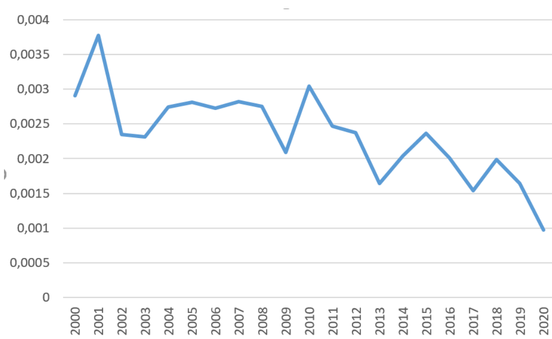

Figure 1: Ratio of publication numbers in VIS-related journals containing the keyword *Medical Visualization* to total number of publications with the same keyword.

cipline 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 in 1986 [1]. Also today, medical datasets are commonly used to benchmark novel visualization techniques, as these provide non-trivial and real-world datasets that can be used as a gold standard for testing.

Although the medical field itself is constantly evolving, there does not seem to be a corresponding increase in published medical visualization papers at our top visualization research venues, as shown in Figure 1. These graphs are generated by the Dimensions website, which allows users to browse research papers according to keywords, authors, and venues. Figure 1 (a) shows the ratio between all publications containing the keyword *medical visualization* and the number of publications with the same keyword, but published in VIS-related journals. We selected the following journals *IEEE Transactions on Visualization and Computer Graphics*, *IEEE Computer Graphics and Applications*, *Computers & Graphics* and *Computer Graphics Forum*. Here we see that the ratio continuously decreases throughout the last 20 years. In comparison to 2000, the ratio decreased by around one third.

This development is in contrast to the continued advances in the medical field. An increasing number of challenges arising from the medical field combined with computational advances in computer science lead to opportunities to develop novel analysis and visualization approaches. In 2012, Botha et al. [1] summarized open challenges in medical visualization. In 2015, IEEE VIS featured a tutorial on Rejuvenated Medical Visualization, where visualization of large-scale data, whole-body data, physiology data, non-standard imaging and simulations, and cohort studies were identified as promising research areas for the future. Since then, some challenges have received attention, while others have evolved. In addition, new challenges arose from rapid developments in computer science, such as the increasing role of AI technologies for medical image analysis.

This article outlines current open challenges in medical visualization from different perspectives. It is based on discussions in our Application Spotlight as well as an informal survey among 14 participants from a wide range of backgrounds from academia and industry. Our aim in highlighting these challenges is to provide an overview and to inspire further 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 multi-valued 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, or lack of consistency in metadata recording, for example. In the following, we discuss open medical visualization challenges arising from the nature of medical data.

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

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

Figure 2: Measurements and computational models are assimilated to improve precision [2].

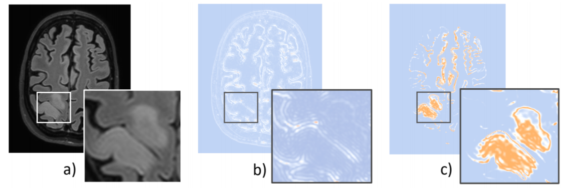

Figure 3: Uncertainty-aware visualization of brain lesions [5].

and identify directions for improvements. In contrast to other disciplines, medical data can usually not be made public easily. Laws demand that any shared data needs to be anonymized and in many cases patient consent is required. 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.

Data curation [3] refers to the organization and integration of data collected from various sources. It also includes the curation of visualization results. Lack of curation results in a significant amount of work which 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 researchers. We could be inspired by the Protein Data Bank (PDB)[2] as used in molecular modeling. Unfortunately, such a unified platform does not exist in the medical area, likely due to lack of standardization and the sensitive nature of medical data.

Data assimilation

Data assimilation [4] is defined as the combination of data and computational models. The idea is to couple the observed data and the underlying dynamical principles governing the system. The idea is to provide an estimate that is better than what could be obtained using just the data or the model alone. This principle arose from environmental sciences where the aim was to enhance climate models and predictions.

De Hoon et al. [2] applied this principle to blood flow, combining measurements and computational models (see Figure 2). 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.

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 areas are 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. To solve this issue, collaborations with researchers from data 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.

Uncertainty

Especially in medicine, where large amounts of data are acquired in order to determine good

[2]https://www.rcsb.org/

treatment strategies, the communication of uncertainty is an important issue to enable proper 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. For modalities where the analysis is performed on derived entities from the measurements, such as PC-MRI or DWI, this become 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. Ristovski et al. [6] discussed how uncertainties arise in different manners when considering medical images. 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 3), but the proper approach needs to be selected and tailored to the use case. This includes three major steps: uncertainty modeling, uncertainty propagation, and uncertainty visualization. A general overview of the state of the art in uncertainty visualization is available in the survey by Bonneau et al. [7].

Multi-modal visualization

Multi-modal data occurs often in the medical context, as clinicians often require different views on a patient in order to derive a suitable 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 4). Lawonn et al. [8] identified open challenges in this area in a state-of-the-art report on multi-modal 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, illustrations, ghosted views, and cutaways were identified as key visualization techniques to identify what is the essential information to reveal from which modality. In addition to multi-modal medical imaging data, heterogeneous data analysis is challenging. Combining data from

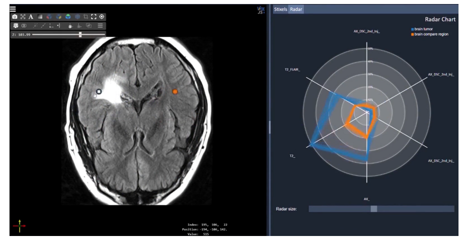

Figure 4: ParaGlyder: multi-parametric brain imaging exploration [9].

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. Multi-scale data refers 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, a 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 multi-modal data, 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.

From one to many

Analysis of entire cohorts of patients becomes increasingly popular as a mechanism to identify how an individual relates to a cohort. Ensemble visualization refers to the visualization of multiple datasets, often resulting in multiple simulation runs or cohort studies. This is closely related to uncertainty visualization and bootstrapping or simulation models are used to represent uncertainty. Ensemble visualization is also required in order to examine differences and similarities among a variety of patients (cohorts). When considering cohorts, the number of datasets can increase dramatically. Wang et al. [10] presented a state-of-the-art report summarizing ensemble visualization approaches. They proposed ways to select a suitable ensemble visualization based on different criteria, such as data type, visualization approach, or analytical task. Ensemble visualization application papers often focus on either imaging data or non-spatial data. As a result, the selection of a suitable visualization approach for a holistic view on such data in the medical context is still an open problem. In addition, computational approaches that are able to handle a large amount of data is required.

Standardization and harmonization

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. The development of rich datasets to serve as gold standards for visualization research is not trivial. Standards should be defined on how data is to be stored, processed and accessed.

For all advanced imaging techniques, standardization and harmonization is a serious problem. For example, for perfusion data, measured blood flow data, spectroscopy, and other special types of MRI data, the results depend not only 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 the number one issue that prevents the widespread use of these advanced modalities and the transformation of research prototypes into products. Guidelines on how to interpret the data are difficult to establish when results are so different between multiple devices. The Surgical Data Science[3] initiative is also discussing the challenge of lacking standardization frequently.

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

Extracting features

Medical data is 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. To understand the knowledge encoded in this data, clinicians need to review these datasets in order to extract the meaning. There exists a variety of approaches to automatically extract features from data, especially in the medical context, but unfortunately such methods often do not work out of the box. In particular, most machine learning techniques reproduce human behavior or are biased towards the data set at hand. 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 is not possible. Instead, visualization approaches that show the original data in comparison to the predicted meaning for decision support are required. The final decision-making is done by humans who need to understand why a system is providing a potential decision. Automatic methods are based on data sets 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 in this respect.

Progressive visual analytics

Zgraggen et al. [11] demonstrated that progressive visualization has a dramatic effect on exploratory data analysis. In the medical field, data is traditionally analyzed in an exploratory fashion. Progressive visualization can assist in reviewing massive amounts of data while updating the visualization according to the progressive sampling of data or performed computations. In a medical context, the evaluation and decision-making process using intermediate results is especially controversial. The user has to be correctly informed on the uncertainty present in the intermediate results such that they can take well-informed decisions. Therefore, specific adaptations of progressive visual analytics methods to medical data are required.

Application domain challenges

The medical application domain provides a specific setting that needs to be considered when designing medical visualization techniques that are intended for clinical use. In contrast to many other visualization 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.

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. Such integrated analysis methods can be achieved by addressing some of the aforementioned data challenges. 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 [12]. 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.

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 generation of new knowledge. Visualization and visual analytics can play a key role in establishing methods for explainable AI (XAI) [13] 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 contributed 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. Under the EU's General Data Protection Regulation (GDPR), people have a right to an explanation of all decisions made by automated or artificial intelligence algorithms[4]. 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 here, for example from pedagogical sciences.

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 provides 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 suitable example was given by Saalfeld et al. [14] (see Figure 5). They used a virtual reality environment to educate medicine student about the anatomy of the hand. 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

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

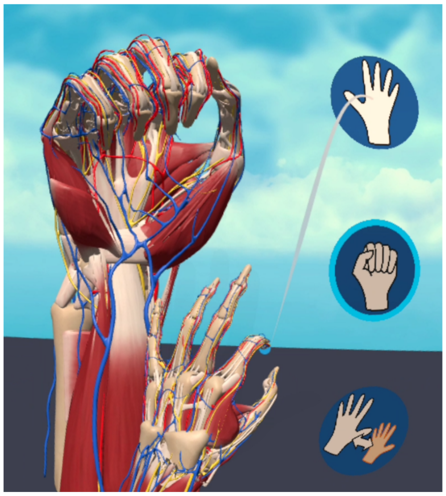

Figure 5: In this educational tool, users can explore anatomy of the hand in VR [14].

visualizations can benefit the medical domain. Particularly educational applications are shown to be effective using augmented and virtual reality. Augmented 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. Further research is necessary to identify the most effective approaches and applications for VR and AR in medical visualization.

General challenges

There exists a set of challenges that arise neither from medical data nor from the application domain specifically, but are generally challenging.

Multidisciplinarity

Medical visualization applications cannot be developed without maintaining a close collaboration with medical experts. Exchange can be complicated by differences in education on both sides and a different vocabulary that is used to express certain processes and different workflows. In addition, there might be additional stakeholders involved in the development of novel visualization approaches, such as companies or clinical administrations. While many multidisciplinary collaborations have been successful, currently there are no guidelines on how to set up and maintain such fruitful partnerships. In addition, the field of medical visualization is not always strongly visible in other fields, which leads to missed opportunities. In order to add to the multidisciplinary challenge even further, neighboring disciplines such as biological data visualization are thoroughly developed, especially in molecular visualization, but bridges to medical data visualization are still lacking.

Evaluation of visualization and data processing

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 a 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 which often does not go beyond anecdotal, in turn leading to hindered acceptance. As such, suitable metrics for medical visualization evaluation [15] need to be defined. Medical visualization researchers could be inspired further by performance measures that go beyond correctness and time, as frequently discussed at the BELIV workshop.

Certification for clinical translation

There is a gap between novel visualization approaches and their usage in application domains. The source of this gap is multifaceted, but an important issue—in addition to standardization—is that many novel visualization approaches need to be certified for clinical use. Especially in the medical domain, this process can take years [16] due to complex and massive regulations that need to be considered for certification. Visualization researchers typically do not have the background or financial resources to execute such a certification process. This typically hinders the use of novel visualization approaches in practice. A first step towards knowledge transfer may be to develop tools for research purposes and aim at uptake by companies that are better positioned to realize translation to clinical practice. However, an open challenge is the fact that commercial vendors will only participate if the visualization technique is in line with their strategy and a large market gain can be expected to justify certification costs.

Data privacy

Independent of their origin, data is usually owned by a person or an institution. This ownership implies rights that need to be considered when aiming to utilize data sources. Unfortunately, there does not exist a general regulation (not even at a country level) 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 under 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.

Ethical considerations

Independent of the application, ethical issues are an increasingly relevant topic. In particular, such issues play a large role when considering machine learning approaches and disease risk information originating from genome analysis. In many applications, it is not clear which knowledge is allowed to be used and who has to give permission to do so. The legal frame surrounding this topic needs further consideration and needs to be adjusted based on novel findings in research. This is an important challenge that will become more prominent in the upcoming years.

Medical training and education

Domain scientists do not always have background knowledge available to immediately grasp complex visualization approaches [17]. Users often need training in order to do so. As long as advanced visualization adds value, such training or a learning curve can still pay off. However, visualization training and onboarding is an important issue when aiming at clinical use.

In addition, medical visualization can actively contribute to medical education, for example, to learn human anatomy [18] (see Figure 5). Here, open challenges are integrating more modalities than 3D visualization, further exploration of the use of VR, and providing adaptive visualizations tailored to the learner.

Unifying software framework

There exists a wide variety of medical visualization prototype applications, covering data-driven, task-driven, and user-driven visualization approaches. Yet, a unified visualization software development framework is missing, which includes existing solutions and can be extended if novel visualization approaches are developed. In this way, existing methods no longer need to be re-implemented for comparison purposes and it becomes easier to extend existing techniques. Such a framework could also strengthen the use of novel visualization techniques by making them more widely available and give researchers new to the field an overview of existing approaches and a starting point for their research.

Community building

The field of medical visualization involves many different stakeholders. Here, researchers (from computer science and medicine) need to collaborate with clinicians, clinics, and companies in order to develop novel visualization approaches. In order to provide a basis for communication and finding a common ground, funding dedicated to community building would be helpful. This funding could assist in organizing events, creating unified databases, data formats, and visualization approaches, or could help collect available approaches in a database that allows for a starting point for researchers on the border between visualization and medicine.

Discussion

Given the open challenges, a question arises if these can be prioritized, or if there are order dependencies between them. Here, we found that many of the challenges can impact developments in related challenges and there is no clear mecha-

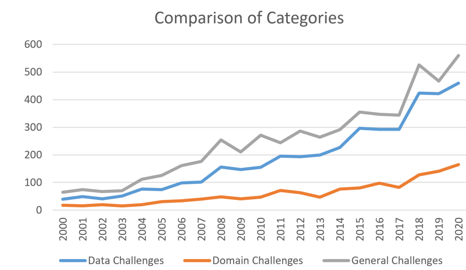

Figure 6: Publications in the three identified main challenge areas for medical visualization.

nism to assess which of the challenges should be addressed first. Many of the challenges are closely interlinked and medical visualization research can cover aspects of a variety of challenges.

Another question is to what degree the outlined challenges are already published on and if any trends can be identified from this. To this end, we explore the total numbers of publications regarding the challenges discussed in this manuscript. Here, we combined each challenge with the keyword *medical visualization* and searched for the number of publications that contain these words as keywords.

Figure 6 reveals the number of publications in the three categories of challenges. Here, we can observe that domain challenges are targeted much less than data challenges and general challenges. The growth in publications in the domain challenges is rather small, indicating that this topic could need more attention. On the other hand, the other challenges become increasingly important, especially since 2017, revealing a flourishing publication environment.

Conclusion

In this manuscript, we outline a set of current open challenges in medical visualization and categorize them as challenges arising from medical data, arising from the application domain, and general medical visualization challenges. We highlight several avenues of exploration to potentially address these challenges and selected contributions in these areas. In medical visualization research, it is often not a single challenge which is targeted but rather a combination of many closely related challenges.

This manuscript is intended to function as a starting point for researchers in medical visualization to understand the open problems in this field and provide key problems that can be tackled to establish a successful research path.

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REFERENCES

1. C. Botha, B. Preim, A. Kaufman, S. Takahashi, and A. Ynnerman, “From individual to population: Challenges in medical visualization,” *Mathematics and Visualization*, vol. 37, 06 2012.
2. 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,” *Computer Graphics Forum*, vol. 39, no. 6, pp. 496–512, 2020.
3. 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*, 2020.
4. 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.), pp. 291 – 311, Boston: Elsevier, 2015.
5. C. Gillmann, D. Saur, T. Wischgoll, K.-T. Hoffmann, H. Hagen, R. Maciejewski, and G. Scheuermann, “Uncertainty-aware Brain Lesion Visualization,” in *Eurographics Workshop on Visual Computing for Biology and Medicine* (B. Kozlíková, M. Krone, N. Smit, K. Nieselt, and R. G. Raidou, eds.), The Eurographics Association, 2020.
6. G. Ristovski, T. Preusser, H. K. Hahn, and L. Linsen, “Uncertainty in medical visualization: Towards a taxonomy,” *Computers & Graphics*, vol. 39, pp. 60 – 73, 2014.
7. G.-P. Bonneau, H.-C. Hege, C. R. Johnson, M. M. Oliveira, K. Potter, P. Rheingans, and T. Schultz, “Overview and state-of-the-art of uncertainty visualization,” in *Scientific Visualization*, pp. 3–27, Springer, 2014.
8. K. Lawonn, N. Smit, K. Bühler, and B. Preim, “A survey on multimodal medical data visualization,” *Computer Graphics Forum*, vol. 37, no. 1, pp. 413–438, 2018.

9. E. Mörth, I. S. Haldorsen, S. Bruckner, and N. N. Smit, "Paraglyder: Probe-driven interactive visual analysis for multiparametric medical imaging data," in *Advances in Computer Graphics*, pp. 351–363, Springer International Publishing, 2020.
10. J. Wang, S. Hazarika, C. Li, and H.-W. Shen, "Visualization and visual analysis of ensemble data: A survey," *IEEE Transactions on Visualization and Computer Graphics*, vol. PP, pp. 1–1, 07 2018.
11. E. Zgraggen, A. Galakatos, A. Crotty, J. Fekete, and T. Kraska, "How progressive visualizations affect exploratory analysis," *IEEE Transactions on Visualization and Computer Graphics*, vol. 23, no. 8, pp. 1977–1987, 2017.
12. B. Preim and K. Lawonn, "A survey of visual analytics for public health," *Computer Graphics Forum*, vol. 39, no. 1, pp. 543–580, 2020.
13. E. Tjoa and C. Guan, "A survey on explainable artificial intelligence (xai): Towards medical xai," *IEEE transactions on neural networks and learning systems*, vol. PP, 2020.
14. P. Saalfeld, A. Albrecht, W. D'hanis, H.-J. Rothkötter, and B. Preim, "Learning hand anatomy with sense of embodiment," 09 2020.
15. B. Preim, T. Ropinski, and P. Isenberg, "A critical analysis of the evaluation practice in medical visualization," in *Workshop on Visual Computing for Biology and Medicine*, 2018.
16. R. G. C. Maack, D. Saur, H. Hagen, G. Scheuermann, and C. Gillman, "Towards Closing the Gap of Medical Visualization Research and Clinical Daily Routine," in *VisGap - The Gap between Visualization Research and Visualization Software* (C. Gillmann, M. Krone, G. Reina, and T. Wischgoll, eds.), The Eurographics Association, 2020.
17. C. Gillmann, T. Wischgoll, J. T. Hernández, and H. Hagen, "Teaching Image Processing and Visualization Principles to Medicine Students," in *IEEE Visualization Conference (VIS) - Pedagogy of Data Visualization Workshop*, 2017.
18. B. Preim and P. Saalfeld, "A survey of virtual human anatomy education systems," *Computers & Graphics*, vol. 71, pp. 132–153, 2018.

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