Visual exploration of intracranial aneurysm blood flow adapted to the clinical researcher

B. Behrendt[1], W. Engelke[2], P. Berg[3,4], O. Beuing[5], I. Hotz[2], B. Preim[1] and S. Saalfeld[1,4]

[1] Department of Simulation and Graphics, University of Magdeburg, Germany
[2] Department of Science and Technology, Linköping University, Sweden
[3] Department of Fluid Dynamics and Technical Flows, University of Magdeburg, Germany
[4] Research Campus *STIMULATE*
[5] Institute of Neuroradiology, University Hospital Magdeburg, Germany

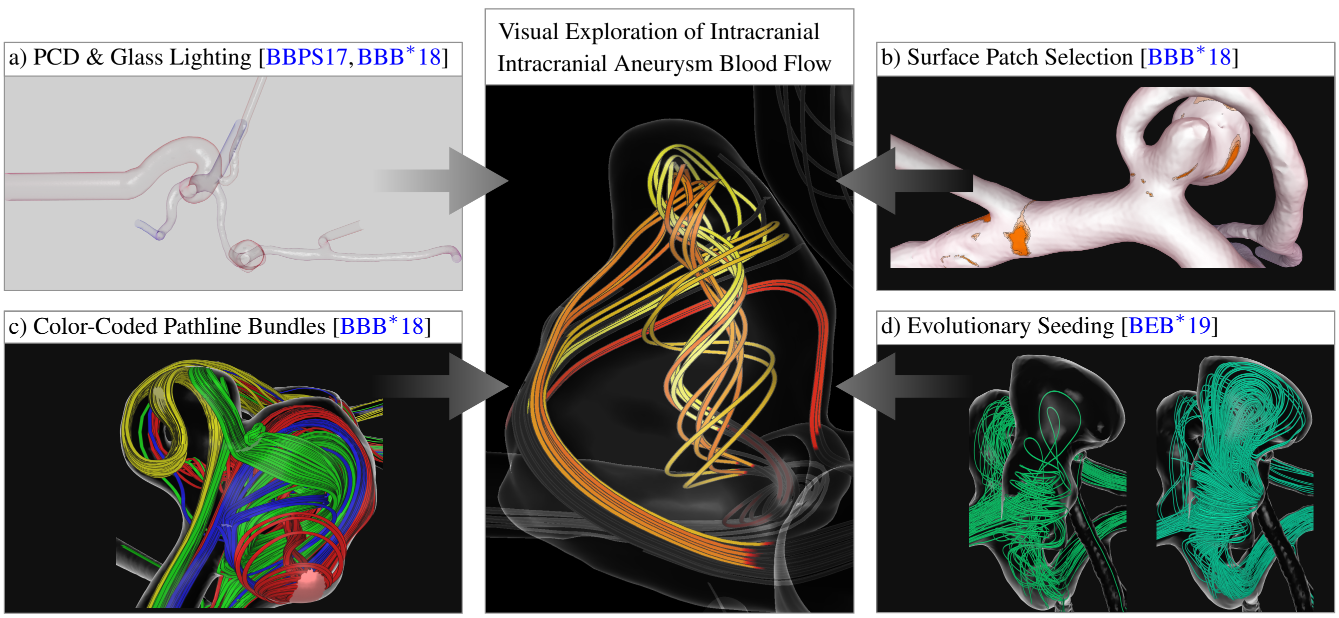

Figure 1: *Components of our visual exploration framework*

Abstract

Rupture risk assessment is a key to devise patient-specific treatment plans of cerebral aneurysms. To understand and predict the development of aneurysms and other vascular diseases over time, both hemodynamic flow patterns and their effect on the vessel surface need to be analyzed. Flow structures close to the vessel wall often correlate directly with local changes in surface parameters, such as pressure or wall shear stress. However, especially for the identification of specific blood flow characteristics that cause local startling parameters on the vessel surface, like elevated pressure values, an interactive analysis tool is missing. In order to find meaningful structures in the entirety of the flow, the data has to be filtered based on the respective explorative aim. Thus, we present a combination of visualization, filtering and interaction techniques for explorative analysis of blood flow with a focus on the relation of local surface parameters and underlying flow structures. In combination with a filtering-based approach, we propose the usage of evolutionary algorithms to reduce the overhead of computing pathlines that do not contribute to the analysis, while simultaneously reducing the undersampling artifacts. We present clinical cases to demonstrate the benefits of both our filter-based and evolutionary approach and showcase its potential for patient-specific treatment plans.

CCS Concepts
• ***Human-centered computing*** → *Scientific visualization;*

1. Introduction

Intracranial aneurysms are pathologic dilatations of the intracranial vessel wall that bear the risk of rupture with fatal consequences for the patient. Since treatment of complex cases might cause a rupture as well, treatment or a monitoring strategy have to be carefully evaluated. Thus, aneurysm rupture risk remains an active research area. Various scores (e.g. PHASES [GWBJ*14], UIATS [EBB*15]) have been developed and postulated to assist interventional neuroradiologists, most of which have pitfalls or do not satisfactorily incorporate hemodynamic analyses. However, quantitative parameters have a large potential for aneurysm analysis [CMWP11] and have been successfully employed to built up an intracranial aneurysm rupture risk prediction model [DCM*18].

Nowadays, there is a large gap between the state of the art in flow visualization with very complex techniques, which are often impractical or simply too overloaded with information for our clinical cooperation partners in daily clinical practice, and the patient-specific analysis of aneurysms at risk. Apart from solely rupture risk assessment, physicians are also interested in the complex interaction between hemodynamics and wall properties. Simply displaying pathlines inside of the vessel anatomy using established smart visibility techniques would therefore likely produce unsatisfactory results. Filtering pathlines based on parameters such as velocity magnitude or vorticity reduces occlusion of the vessel surface, thus allowing both to be displayed in the same view. However, in an explorative scenario where the physician wants to figure out what kind of flow causes a specific phenomenon on the vessel surface, the use of such filters can be obstructive.

2. Related Work

Various methods have been developed explicitly for the explorative visualization of medical flow data [OJMN*18]. Geometry-based techniques, such as streamlines or pathlines, are the most frequently used methods for flow analysis [MLP*10]. The biggest challenge of these methods is to avoid clutter and occlusion without missing important features in the data, as interesting structures, such as vortices, are often hidden within more laminar flow. Born et al. adapted line predicates to support the exploration of cardiac blood flow by designing a set of predefined predicates [BPM*13]. Günther et al. [GRT13] presented an implicit filtering approach which modulates the line transparency with respect to view-dependent occlusion and an importance criterion. A common issue with filtering approaches is the dismissal of a high percentage of the calculated lines, which is unfavorable in cases where the line integration is expensive. Van Pelt et al. [vBB*11] include dynamic seeding capabilities in their explorative framework to overcome this issue. Similarly, de Hoon et al. [dHLJ*19] use particles to simulate injecting ink into a vessel at a specific location. To automatically determine potentially interesting seeding locations in a flow field, Broos et al. employ user-defined transfer functions [BHK*16].

3. Visual Exploration Techniques

We present a set of techniques to interactively find flow structures based on *desired properties* or their *effect on the vessel wall*. Regions on the wall can be directly selected based on their hemodynamica parameter values. Additional visualization tools, such as a perception-oriented pseudo-chromadepth color overlay [BBPS17], support this approach.

3.1. Surface-based Pathline Filtering

Our work [BBB*18] was designed in cooperation with an experienced neuroradiologist to identify complex interactions between hemodynamic parameters in general, and combines the tasks of parameter visualization and pathline selection to create an intuitive and robust tool for explorative pathline filtering.

Vessel Visualization and Surface Patch Selection

Initially, the user is presented with an empty visualization of the vessel surface. To prevent the surface from occluding the inner flow that the user will eventually add, we implemented a *glass lighting* approach to facilitate a transparent visualization (Fig. 1a). Similar to the approach by Gasteiger et al. [GNKP10], the lighting intensity is multiplied with the vessel opacity for each vertex, although we consider both the traditional Phong lighting as well as an additional Fresnel mask for this. To support depth perception a psuedo-chromedepth color overlay can be enabled, tinting the vessel edges using a depth-based color gradient ranging from red to blue (Fig. 1a) [BBPS17].

To add pathlines to the visualization, the user has to select at least one area ("*patch*") on the vessel surface based on surface parameters. For this task the surface is rendered fully opaque with parameters mapped using a color scale. In order to highlight interesting hotspots, which are characterized by local extrema of surface parameter values, we employ discretized color scales with black boundaries between the shades (Fig. 1b). The user can freely choose from a set of predefined color scales and configure the amount of discrete shades. A surface region can be selected from this visualization by clicking on the vessel. The application will determine the closest surface vertex to the curser and, based on the users' preference, select all adjacent vertices *with the same shade* or *within a fixed distance*, i. e. a circular patch.

Pathline Visualization

After the user completes the selection of interesting surface regions, the surface visualization reverts to *glass lighting*. Users can now choose a distance to extract pathlines from. Only pathlines where at least one vertex is within the selected distance to the surface patch is included in the line bundle associated with that patch. If the user has selected multiple patches on the surface, the distance threshold can be configured individually for each patch and the resulting pathline bundles are colored according to the patches they belong to (Fig. 1c).

To further refine the previously selected lines, pathline bundles can be filtered based on their parameters, such as pressure or velocity. One way of filtering the bundles is to map their hemodynamic parameters to line thickness or opacity, effectively reducing the visibility of lines with certain high or low parameter values. Instead of implicitly filtering pathlines using thickness or opacity, the user can explicitly select parameter ranges in a scatterplot, parallel coordinates view or line chart of the current pathline bundle by drawing a selection rectangle.

Flow Statistics Calculation and Report Generation

Based on feedback from our collaborating physicians, we added the option to calculate various quantitative measures concerning both the selected patches and associated pathline bundles, and export them in a standardized manner. For *patches*, we calculate the surface area and average values for all available hemodynamic parameters over the entire patch. For *pathline bundles* associated to the patches, we calculate the average flow velocity over all pathlines of the bundle. As the physicians are often specifically interested in the flow velocity within the aneurysm, we additionally compute the average flow velocity of the pathline sections between entering and leaving the aneurysm. The average velocity of pathline bundle sections close to the respective surface patch are also displayed based on default distances which can be freely configured. These values are calculated individually for each surface patch and exported either as a CSV file or together with an automatically generated screenshot of the patch and pathlines as a PDF report.

3.2. Evolutionary Pathline Generation

Many existing approaches rely on filtering pre-integrated pathlines. Especially for instationary flow, the seed points for *interesting* pathlines are often sparsely distributed in the seeding domain and can therefore easily be missed, even when seeding a high amount of pathlines. Thus, high computational costs are required for pathlines that will never be shown, while still having no guarantee to find the features of interest. Recently, Engelke et al. [EH18] introduced evolutionary streamlines for the analysis of steady flows. This approach is extended and adapted for the integration in our exploration framework to generate evolutionary pathlines [BEB*19]. A set of predefined fitness functions supports the automatic extraction of a set of representative pathlines for flow patterns of patient groups with high anatomical variations, including aneurysm blebs or strongly lobulated shapes. The input to the evolutionary algorithm is the aneurysm geometry and the simulated blood flow. For each iteration ("*generation*"), the evolutionary algorithm generates a set of pathlines and evaluates each line based on user-defined fitness criteria. This set consists of the best lines from the previous generation ("*elite*"), modified variations of good lines from the previous generation ("*mutation*") and newly generated random lines ("*insertion*"). This cycle continues for a set number of iterations, or until a specific average fitness of the current pathline generation is reached.

A plane is automatically fitted in the vessel inlet, which serves as seeding plane for the pathline generation. The genome of the individuals encodes a single seed point $I_i = (x_i, y_i)$ in the local coordinate system of the seeding plane, which uniquely defines a pathline with respect to the integration settings. New individuals are always initialized with random values in their genome, i.e. spawn from a random position on the seed plane. Mutation is facilitated by a weighted displacement vector $\vec{d} \in [-1.0, 1.0]^d$ to the individual's genome; here, d is the dimension of the search space. To evaluate the fitness of an individual, the entire pathline has to be integrated from its seed point. The fitness function $f(I_i)$ is assembled from a set of local properties $f_1..f_n$. The properties are comprised of fitness information based on pathline geometry (such as length or curvature) and fitness information based on attributes of the vessel surface close to the pathlines (such as pressure or wall shear stress). Both length and curvature of a pathline can indicate the presence of vortex structures, as a pathline is often longer and has higher curvature when passing through a vortex. Additionally, all indicator values for pathline vertices outside the aneurysm can be disregarded, effectively preventing surface attributes outside of the aneurysm from contributing to the fitness of a line. Each local pathline property $f_p(I_i)$ is assembled from the per-vertex fitness indicators v_{ij}. The final fitness value for a pathline is the weighted combination of all its pathline properties.

4. Evaluation

To evaluate our surface selection method, we asked two experienced neuroradiologists (*Physician A*, who was involved in the design process of our framework, and *Physician B*) and an expert in flow simulation to apply it to nine aneurysms and recorded their findings. All three experts described our method as an advancement in the field of explorative flow visualization. All experts described our method as an advancement in the field of explorative flow visualization. They were able to quickly find interesting surface regions that almost always yielded interesting flow patterns such as vortices when selected. The color-coding proved especially useful for assessing which adjacent vessels a particular flow pattern drains into. According to the experts, a precise selection of specific flow patterns based on their relation to surface features has previously not been possible. They highly appreciated the visualization of splitting flow. Overall, our combination of interaction, visualization and filtering techniques allows for systematic exploration and qualitative assessment of flow structures.

Physician A was primarily interested in patches with either high or low normalized wall shear stress or high OSI. To facilitate comparability between datasets, the expert used similar or identical parameter ranges for the placement of surface patches and the extraction of pathlines. The expert also used the line chart to determine if a pathline bundle contains more than one actual vortex structure by plotting the residence time over flow distance. Since settings, such as mapped surface parameter, number of color scale shades or custom parameter ranges were reset to a default value when switching between datasets, he wished for a way to change the default values or create custom presets to accelerate the process of placing patches. *Physician B* was primarily interested in visualizing splitting flow in aneurysms for the purpose of optimal flow diverter placement. While experienced neuroradiologists are often able to infer this information from the wall geometry alone, visualizing the splitting flow could be a valuable help to less experienced neuroradiologists. Since the expert had limited interest in correlating flow structures with surface parameters, she mostly placed patches based on geometric features, such as blebs or the aneurysm dome.

All experts expressed their interest in being able to further quantify various aspects of their exploration results, such as measuring the size and extent of detected structures. More complex measures, such as the amount of flow that passes through a certain structure or directly underneath a surface patch, would be desirable as well. Another requested feature was the ability to place a plane into the parent vessel of an aneurysm and map the attributes and spatial positions of pathlines passing through it to generate a flow profile.

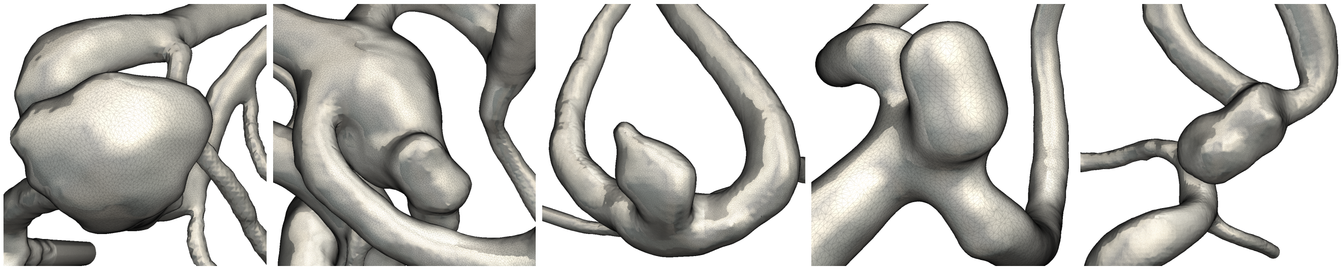

Figure 2: *Selected cases for our evaluation.*

	Physician C	*Physician D*	*Physician E*
Case 1 - before	C & S	C & S	Y – S
Case 1 - after	C & S	C & S	C & S
Case 2 - before	Y – S	C & S	Y – S
Case 2 - after	Y – S	C & S	Y – S
Case 3 - before	C	C & S	Y – S
Case 3 - after	C	Y – S	C & S
Case 4 - before	Y – S	C & S	Y – S
Case 4 - after	Y – S	Y – S	Y – S
Case 5 - before	Y – S	C & S	Y – S
Case 5 - after	Y – S	Y – S	Y – S

Table 1: *Results of our evaluation for physicians C, D and E, when only seeing anatomical information (before) and after seeing our pathline visualization (after). Treatment decisions were: stent-assisted coiling (C & S), y-stenting (Y–S), and coiling without stenting (C). Changes in treatment decisions are highlighted.*

For the evolutionary line seeding approach, we performed a general evaluation with *Physician A*. Afterwards, we conducted a more specific evaluation with three additional neuroradiologists (*Physician C*, *Physician D* and *Physician E*), who were not familiar with our tool, to validate its clinical usefulness with respect to treatment planning. Our goal was to evaluate

1. which fitness function configuration produces the most satisfactory line bundles for this purpose.
2. whether the visualization of hemodynamic information using evolutionary pathlines influences the treatment decision.

To answer question 1, we asked *Physician A* to compare the resulting lines of different fitness functions. The comparison consisted of pathlines optimized for length and to pass by surface areas in the aneurysm with high and low WSS as well as high and low OSI. The physician was able to easily identify differences between line bundles optimized with respect to high or low OSI and even infer the location of high and low OSI or WSS values on the surface. To evaluate the blood flow for treatment decisions, he preferred the length-based fitness function, as it ensured that the entire aneurysm was filled with pathlines (Fig. 1d).

To answer question 2, we presented the other experts (*Physician C-E*) with five challenging cases (Fig. 2), which were selected from a database containing more than 100 cerebral aneurysms with the help of *Physician A*.

The first visualization only depicted the vessel surface without any hemodynamic information. The physicians were asked about their treatment decision based on the given visualization. Afterwards, we presented them with the same dataset, including pathlines extracted by the evolutionary algorithm, and asked whether they would revise their decision. For this evaluation, we chose a fitness function based on both line length and residence time of the flow inside the aneurysm, as it achieves a pathline coverage superior to uniform seeding approaches and covers the whole aneurysm. In four of five cases, at least one physician changed his or her treatment decision after exploring our evolutionary pathlines (Table 1). These changes were motivated by an improved understanding of the intra-aneurysmal flow and its splitting into the outlets, including flow patterns. In three cases, these changes lead to more consistency in the final decision between the physicians. The third aneurysm was the most challenging one, as two physicians changed their minds and the final decisions are not consistent between them. On the one hand, their initial decisions were similarly inconsistent, but on the other hand, we selected challenging cases. Interestingly, the most experienced physician never changed his mind.

5. Conclusions

We have presented a set of intuitive techniques to allow for an interactive exploration of local blood flow based on surface features. The clinical experts appreciated the local selection techniques to analyze blood flow characteristics in combination with surface parameters. The use of evolutionary algorithms offers significant improvements over existing seeding strategies, both in terms of computational effort and quality of results, such as better coverage of hemodynamically interesting regions (aneurysm domes or blebs). If the users feel that a certain interesting area is under-detailed due to a lack of pathlines, they may dynamically add pathlines specifically tailored to their needs.

At the moment, our toolset is only focused on the exploration of a single dataset. To better support comparisons, further quantitative values in addition to the existing ones should be extracted, for example about the flow directly underneath a patch or the patch itself. Instead of simply showing multiple datasets side-by-side in isolated views, an integrated visualization would be desirable. Due to the complex geometry structure of intracranial vessels and flow structures, the visualization could additionally benefit from the emersion provided by virtual reality [BPS*20].

References

[BBB*18] BEHRENDT B., BERG P., BEUING O., PREIM B., SAALFELD S.: Explorative blood flow visualization using dynamic line filtering based on surface features. *Computer Graphics Forum 37*, 3 (2018), 183–194. 1, 2

[BBPS17] BEHRENDT B., BERG P., PREIM B., SAALFELD S.: Combining pseudo chroma depth enhancement and parameter mapping for vascular surface models. In *Eurographics Workshop on Visual Computing for Biology and Medicine* (2017), The Eurographics Association. 1, 2

[BEB*19] BEHRENDT B., ENGELKE W., BERG P., BEUING O., PREIM B., HOTZ I., SAALFELD S.: Evolutionary pathlines for blood flow exploration in cerebral aneurysms. In *Eurographics Workshop on Visual Computing for Biology and Medicine* (2019), The Eurographics Association. 1, 3

[BHK*16] BROOS A. J. M., HOON, NIELS H. L. C. DE, KONING, PATRICK J. H. DE, GEEST, ROB J. VAN DER, VILANOVA A., JALBA A. C.: A Framework for Fast Initial Exploration of PC-MRI Cardiac Flow. *Proceedings of the Eurographics Workshop on Visual Computing for Biology and Medicine* (2016), 69–78. 2

[BPM*13] BORN S., PFEIFLE M., MARKL M., GUTBERLET M., SCHEUERMANN G.: Visual analysis of cardiac 4D MRI blood flow using line predicates. *IEEE transactions on visualization and computer graphics 19*, 6 (2013), 900–912. 2

[BPS*20] BEHRENDT B., PIOTROWSKI L., SAALFELD S., PREIM B., SAALFELD P.: The virtual reality flow lens for blood flow exploration. In *Eurographics Workshop on Visual Computing for Biology and Medicine* (2020), The Eurographics Association, pp. 37–41. 4

[CMWP11] CEBRAL J. R., MUT F., WEIR J., PUTMAN C.: Quantitative characterization of the hemodynamic environment in ruptured and unruptured brain aneurysms. *American Journal of Neuroradiology 32*, 1 (2011), 145–151. 2

[DCM*18] DETMER F. J., CHUNG B. J., MUT F., SLAWSKI M., HAMZEI-SICHANI F., PUTMAN C., JIMÉNEZ C., CEBRAL J. R.: Development and internal validation of an aneurysm rupture probability model based on patient characteristics and aneurysm location, morphology, and hemodynamics. *International journal of computer assisted radiology and surgery 13*, 11 (2018), 1767–1779. 2

[dHLJ*19] DE HOON N., LAWONN K., JALBA A., EISEMANN E., VILANOVA A.: Inkvis: A high-particle-count approach for visualization of phase-contrast magnetic resonance imaging data. In *Eurographics Workshop on Visual Computing for Biology and Medicine* (2019), pp. 177–188. 2

[EBB*15] ETMINAN N., BROWN R. D., BESEOGLU K., JUVELA S., RAYMOND J., MORITA A., TORNER J. C., DERDEYN C. P., RAABE A., MOCCO J., ET AL.: The unruptured intracranial aneurysm treatment score: a multidisciplinary consensus. *Neurology 85*, 10 (2015), 881–889. 2

[EH18] ENGELKE W., HOTZ I.: Evolutionary Lines for Flow Visualization. In *EuroVis - Short Papers* (2018), pp. 7–11. 3

[GNKP10] GASTEIGER R., NEUGEBAUER M., KUBISCH C., PREIM B.: Adapted surface visualization of cerebral aneurysms with embedded blood flow information. In *VCBM* (2010), pp. 25–32. 2

[GRT13] GÜNTHER T., RÖSSL C., THEISEL H.: Opacity optimization for 3d line fields. *ACM Transactions on Graphics 32*, 4 (2013), 1. 2

[GWBJ*14] GREVING J. P., WERMER M. J., BROWN JR R. D., MORITA A., JUVELA S., YONEKURA M., ISHIBASHI T., TORNER J. C., NAKAYAMA T., RINKEL G. J., ET AL.: Development of the phases score for prediction of risk of rupture of intracranial aneurysms: a pooled analysis of six prospective cohort studies. *The Lancet Neurology 13*, 1 (2014), 59–66. 2

[MLP*10] MCLOUGHLIN T., LARAMEE R. S., PEIKERT R., POST F. H., CHEN M.: Over Two Decades of Integration-Based, Geometric Flow Visualization. *Computer Graphics Forum 29*, 6 (2010), 1807–1829. 2

[OJMN*18] OELTZE-JAFRA S., MEUSCHKE M., NEUGEBAUER M., SAALFELD S., LAWONN K., JANIGA G., HEGE H.-C., ZACHOW S., PREIM B.: Generation and Visual Exploration of Medical Flow Data: Survey, Research Trends and Future Challenges. *Computer Graphics Forum 40*, 4 (2018), 860. 2

[vBB*11] VAN PELT R., BESCÓS J. O., BREEUWER M., CLOUGH R. E., GRÖLLER M. E., ROMENIJ B. T. H., VILANOVA A.: Interactive virtual probing of 4d mri blood-flow. *IEEE transactions on visualization and computer graphics 17*, 12 (2011), 2153–2162. 2