Wall shear stress calculations using phase contrast MRI

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Chapter 8

Multi-scale 3D+t intracranial aneurysmal flow vortex detection

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8.1 Introduction

Estimations of cerebral aneurysm prevalence range between 0.4% and 6% (1). Cerebral aneurysms have a low acute rupture risk, however, rupture results in aneurysmal subarachnoid hemorrhage and is associated with high mortality and morbidity (2). Treatment is based on excluding the aneurysm from circulation, thereby relieving the aneurysm from hemodynamic stress. Currently, endovascular coil embolization is the first therapeutic option. Although widely practiced, significant peri- and postoperative complications can occur due to these treatments (3, 4). These complications have to be carefully balanced against the risk of rupture to determine the choice of treatment.

In current clinical practice, only size and location are considered in the decision to treat. Additional risk factors are needed for more accurate estimations of aneurysmal rupture risk. Intra-aneurysmal hemodynamic risk factors for aneurysmal growth and rupture have been addressed in many studies. Both low and high wall shear stress (WSS) have been associated with aneurysmal growth and rupture (4-5). Furthermore, unstable flow patterns were associated with aneurysm progression and rupture because of the potential for elevated oscillatory shear index (OSI) or larger regions of elevated mean WSS. In various studies, computational fluid dynamics (CFD) simulations have been performed on vascular models to associate rupture status with flow complexity, flow stability, and inflow jet size (6). Alternatively, intra-aneurysmal velocity can be measured using time-resolved 3D phase contrast MRI (PC MRI) (7). In a recent study, it was shown that ruptured aneurysms had complicated flow patterns in the aneurysm domes, whereas all of the unruptured cases showed a simple vortex (8).

Vortex characteristics such as vortex complexity, vortex stability and flow pattern category are assessed by visual inspection (9). In clinical research studies, intra-aneurysmal flow is commonly categorized according to the definitions previously introduced (9) using animations of intravascular flow velocities: i) constant direction of inflow jet with a single associated vortex, ii) constant direction of inflow with multiple and constant number of associated vortices, iii) changing direction of inflow jet with a single vortex, and iv) changing direction of inflow jet with the creation and destruction of multiple vortices. Illustrations of these flow categories can be found in (9) and are proposed here in Figure 8.1.

Type i flow is associated with unruptured status, whereas type iii and type iv flow is more common in ruptured aneurysms. This classification is well accepted among the community and has been used in multiple clinical studies (9-14). Because of the qualitative and manual assessment, these measurements are prone to interobserver variation. In a recent study of this research group, interobserver agreement was poor with intraclass correlation coefficients ranging from 0.47 to 0.70. Quantitative analysis of vortex characteristics has the potential to reduce interobserver variability and to improve the value of these parameters in risk assessment because of its continuous characteristic as opposed to the classification in a limited number of categories.

8.2 Methods

Hemodynamics, which can be assessed by CFD and PC MRI, are generally presented as time-resolved 3D velocity fields ($\vec{v}(\vec{x}, t)$). Below, we describe approaches to obtain quantitative information from these velocity fields.
8.2.1 Kernel deconvolution

The most commonly applied approaches for vortex detection are the $Q$- and $\lambda_2$-criteria (15). These approaches are based on local pressure characteristics. However, in our experience these criteria do not reflect the impression of radiologists of intra-aneurysmal vorticity because the radiologists interpret more global features. Bauer et al. described various methods for flow field feature visualization (16) and to trace the flow field in time. They used combinations of feature detection techniques, such as vortex core lines detection, with methods acting on the Jacobian of the flow field. Schafhitzel et al. presented an overview on analysis of shear stress layers in flow fields and described a visualization method for simultaneous tracking of vortices and shear layers as well as their interaction (17). More recent studies focus on vortex core lines and vorticity magnitude detection and their variation in time (18, 19). However, in clinical studies, analyses of aneurysmal vortex structures are still based on qualitative visual interpretation and a quantitative measure is still missing.

Furthermore, we noted that the $Q$- and $\lambda_2$-criteria are sensitive to high velocity gradients without an actual circular movement in, for example, aneurysmal neck areas. As such, we searched for more global descriptive methods that are able to capture the clinician’s impression of intra-aneurysmal vorticity. Previously, we have presented a 2D singular velocity pattern detection technique to analyze 2D velocity fields (20) based on the works of Liu and Ribeiro (21). This approach included vortex identification as one of the singular flow patterns. Here, this technique is extended to time-resolved 3D velocity fields. For this new approach, the local velocity field $\vec{v}(\vec{x}, t)$ in a small neighborhood $\Delta \vec{x}$ is represented by a combination of base functions $\vec{\phi}_k(\Delta \vec{x})$

$$\vec{v}(\vec{x}, t) = \sum_k A_k(\vec{x}, t) \vec{\phi}_k(\Delta \vec{x})$$

where the projection coefficients $A_k$ are given by the cross-correlation of the global velocity field.
Multi-scale 3D+intracranial aneurysmal flow vortex detection

Figure 8.2: Local velocity field base functions describing local laminar velocity (top row) and vortical velocity (bottom row). The length and color of the arrows depict the velocity strength. The center of the base functions is at \((0.5 \text{ mm}, 0.5 \text{ mm}, 0.5 \text{ mm})\).

and the base functions

\[
A_k(\vec{x}, t) = \int \vec{v}(\vec{x} + \vec{\xi}, t) \cdot \vec{\phi}_k(\vec{\xi}) d\vec{\xi}
\]  

(8.2)

Because we focus on vortex quantification in this study, only 6 base functions are used; 3 for describing the laminar flow \(\vec{\phi}_k(\Delta \vec{x}) = \hat{e}_k\) for \(k = 1, 2, 3\) with \(\hat{e}_k\) the Cartesian basis vectors where their dimension is \(\text{m/s}\). This part of the velocity field is called laminar flow since it describes the local ‘non-singular’ velocity. The vortex base functions are a single class of the ‘singular’ velocity patterns. This term is called singular because of its diminishing contribution at \(\xi = 0\). We refer to Liu and Ribeiro (21) for illustrations of different singular flow patterns. The three vortex projection coefficients are determined using the following equation

\[
A^v_i(\vec{x}, t) = \int \vec{v}(\vec{x} + \vec{\xi}, t) \cdot (\hat{e}_i \times \vec{\xi}) d\vec{\xi}
\]  

(8.3)

where we have used the superscript \(v\) to indicate that these contributions are the vortex projections. The used base functions are illustrated in Figure 8.2.

8.2.2 Multi-scale space representation

To introduce a finite support size of the base functions and to be able to distinguish various scales of the vorticity, the analyses are performed in a multi-scale space approach. Multi-scale techniques operate on a source signal by a convolution with a Gaussian function (16). With increasing scale, smaller-scale details in the signal are removed. To assess the scale dependent flow patterns, we employ the 3D Gaussian function:

\[
G(\vec{x}, \sigma) = \frac{1}{(\sigma \sqrt{2\pi})^3} \cdot e^{-\frac{||\vec{x}||^2}{2\sigma^2}}
\]  

(8.4)

where \(\sigma\) is the scale. The scale-space dependent velocity field \(\vec{f}(\vec{x}, \sigma, t)\) can be obtained by the convolution of the Gaussian function with the velocity field \(\vec{f}(\vec{x}, \sigma, t) = \vec{v}(\vec{x}, t) \ast G(\vec{x}, \sigma)\). Using the multi-scale approach, we can write the kernel equations as a decomposition of scale-dependent base functions \(\vec{\phi}_{k}(\Delta \vec{x}, \sigma)\), which are defined as the convolution of the initial base functions with
the Gaussian function $\vec{\phi}_k(\Delta \vec{x}) * G(\Delta \vec{x}, \sigma)$:

$$\vec{f}(\vec{x}, \sigma, t) = \sum_k A_k(\vec{x}, t, \sigma) \vec{\phi}_k(\Delta \vec{x}, \sigma)$$

(8.5)

Again, the scale-dependent projection coefficients are determined by the convolution of the velocity field with the scale dependent base functions:

$$A_k(\vec{x}, t, \sigma) = \int \vec{v}(\vec{x} + \vec{\xi}, t) \cdot \vec{\phi}_k(\vec{\xi}, \sigma) d\vec{\xi}$$

(8.6)

Following the method by Marquering et al., we scale the singular projection coefficients by the magnitude of the laminar contributions to correct for the large range of flow magnitudes that can be present within intracranial aneurysms, and to avoid obscuring singular flow patterns at location with low velocities (20). $A_k^v(\vec{x}, t, \sigma)$ represents the vortex magnitude in the $x$-, $y$-, and $z$-direction for $k$ 1, 2 or 3 respectively. As such, the axis of the vorticity is given by the vector $(A^v_1, A^v_2, A^v_3)$ and the vortex magnitude $|A|$ by $\sqrt{A^v_1^2 + A^v_2^2 + A^v_3^2}$.

Note that the scale $\sigma$ and the neighborhood $\Delta \vec{x}$ are related: The larger the scale, the larger the neighborhood with non-zero contributions of the velocity field. In computational practice, the neighborhood is defined as $3 \times \sigma$ in all directions.

### 8.2.3 Vortex-shear discrimination

The kernel deconvolution method described above is suitable for vortex (center) detection. However, it is unable to discriminate vortex fields from shear fields. For this reason, it is necessary to differentiate vortex dominated flow fields from shear dominated flow fields. The widely used $Q$-criterion based on the decomposition of the Jacobian $\vec{J}(\vec{x}, t)$ is commonly used for this task (15), where the Jacobian is defined as:

$$\vec{J}(\vec{x}, t) \equiv \nabla \vec{v}(\vec{x}, t) = \vec{S}(\vec{x}, t) + \vec{\Omega}(\vec{x}, t)$$

(8.7)

with

$$S_{ij} = \frac{1}{2} \left( \frac{\partial v_i}{\partial x_j} + \frac{\partial v_j}{\partial x_i} \right)$$

(8.8)

and

$$\Omega_{ij} = \frac{1}{2} \left( \frac{\partial v_i}{\partial x_j} - \frac{\partial v_j}{\partial x_i} \right)$$

(8.9)

where $S$ denotes the rate of strain and $\Omega$ represents the rotational part of the velocity field. In Equation 8.8 and Equation 8.9 we omitted the dependencies $\vec{x}$ and $t$ for brevity. To take scale into consideration, Equation 8.7 is modified as follows:

$$\vec{J}(\vec{x}, \sigma, t) = \nabla (\vec{v}(\vec{x}, t) * G(\vec{x}, \sigma)) = \vec{v}(\vec{x}, t) * \nabla G(\vec{x}, t)$$

(8.10)

This way, we take advantage of scale space properties and perform the convolution with the derivative of the Gaussian function instead of deriving the velocity field. Vortex dominated areas are detected as regions where $||\Omega(\vec{x}, \sigma, t)|| > ||S(\vec{x}, \sigma, t)||$, which is known as the $Q$-criterion (15). Because the result of the $Q$-criterion is binary rather than a continuous measure, Schafhitzel et al. suggested to use the second invariant of $S$ as a continuous measure for high shear stress region
Multi-scale 3D+t intracranial aneurysmal flow vortex detection

8.2.4 Kernel deconvolution with \(Q\)-criterion masking

To come to a vortex identification and quantification method that excludes shear fields, we here combine the \(Q\)-criterion and the kernel deconvolution analysis. We propose to use the \(Q\)-criterion to create a mask applied to kernel deconvolution results such that we remove shear dominated areas. To depict centers of vortices, local spatial maxima of the vortex magnitude for a given time and scale are detected using a 26-connected neighborhood. The time resolved multi-scale kernel deconvolution with \(Q\)-criterion masking is called ‘kernel deconvolution with \(Q\)-masking’ in the remainder of this paper. The purpose of this method is to visualize, quantify, and discriminate 3D velocity features both in time and in scale to support clinicians in their treatment decisions. The method is evaluated in the comparison of CFD and time-resolved 3D PC MRI data of an aneurysm phantom and patient-specific aneurysmal CFD flow data of 3 patients described below.

![Figure 8.3: Surface rendering of the 3 patient aneurysms used in this study.](image)

8.2.5 Phantom data

The aneurysm phantom was based on an intracranial aneurysm located in the anterior communicating artery. The maximal dimensions of the dome were approximately 6, 4 and 9 mm in the \(x\), \(y\), and \(z\) direction respectively. The phantom was connected to a flow loop setup. Details on this phantom can be found in (22).

Time-resolved 3D PC MRI data of the phantom was obtained using three-directional velocity encoding on an 3 T MR scanner (Intera, Philips Medical Systems, Best, the Netherlands). Additional scanner specific settings were previously reported in (22). The measurement was performed within 3 hours. Spatial resolution was \(0.2 \times 0.33 \times 0.2 \text{ mm}^3\).

CFD simulations (Fluent 6.3, ANSYS, Canonsburg, USA) were performed on a vascular model based on a 3D Rotational Angiogram of the phantom with an isotropic resolution of 0.16 mm. This image was segmented with a level set algorithm (23). A mesh was created consisting of 742,316 tetrahedral cells with an average node spacing of 0.24 mm. The 3D velocity profile of the inflow as
measured in the PC MRI measurements was applied as boundary condition in the CFD. The MRI and CFD data sets were registered using a rigid transformation and interpolated on a 3D isotropic 0.2 mm grid.

8.2.6 Patient data

The patient-specific vessel models for CFD-based flow data in the three patients were generated using 3D rotational angiography imaging (see Figure 8.3). The vascular tree was segmented using a level set algorithm (VMTK). The segmentations were converted into a tetrahedral elements mesh with an average node spacing of 0.07 mm. CFD boundary velocities were based on time-resolved three-directional single-slice PC MRI acquisitions in the afferent artery. CFD simulations were performed using the PC MRI velocity measurements as boundary condition (7). Three cardiac cycles were calculated of which the last cycle was used for analysis. Because of the limited temporal resolution of the MR measurements, only 36 time frames per cardiac cycle were determined resulting in 36 timeframes for the CFD with an average time step of 0.028 s. CFD iterations were continued until the continuity residual was below 0.001.

Figure 8.4: Employed analysis pipeline for flow feature analysis. The 3D-t velocity data consisted of either phantom CFD or MR data or patient CFD velocity data. Vortex centers were detected for two scales and rendered in 3D. At these locations 2D orthogonal slices with velocity profiles were generated inspect the vortex behavior. By monitoring this behavior for all time steps, the stability of the vorticity was assessed. A similar approach was followed to assess the shear stress analysis using the $S_m$-criterion.

8.2.7 Experiments overview

The phantom and patient velocity data sets were processed to detect dynamic and scale-dependent vortices and shear stresses using the kernel deconvolution with $Q$-masking and the $S_m$-criterion respectively. The analysis was conducted for two scales: a small scale with $\sigma = 0.28$ mm, which is similar to the resolution of our datasets, and a large scale with $\sigma = 1.00$ mm, which reflects the dimension of the intracranial arteries. A schematic overview of the analysis pipeline is presented in Figure 8.4. Using the kernel deconvolution with $Q$-masking, vortex centers were detected for a given scale and time step. Simultaneously, shear stress regions were detected. These regions were rendered in 3D. At local maxima of the masked kernel deconvolution, three orthogonal 2D slices
were generated to visualize the flow in detail at these positions. Vortex and shear stress evolution during the heart cycle was subsequently tracked to study the vortex stability.

## 8.3 Results

### 8.3.1 Kernel Deconvolution with $Q$-masking: Phantom Data

Figure 8.5 shows the results of the PC MRI and CFD velocity field analysis in the aneurysm phantom measured for a single time step and scale of $\sigma = 0.28$ mm. The direction of the arrows in the 3D rendering figures denotes the vortex axis of rotation, the length and color represents the vortex magnitude. This 3D view allows a quick overview of flow characteristics. In one of the vortex cores, 2D slices are generated to inspect detection results and explore the region of interest in more detail. The blue small arrows in the 2D planes depict the flow velocity within that plane. Figure 8.6 shows that the flow indeed rotates around the detected vortex center. As can be seen in this figure, two main vortex areas are located in the central part of the aneurysm for both imaging modalities. Comparison of the analysis of the CFD and MRI generated velocity fields indicates that there is only a small difference in direction and magnitude, suggesting that MRI- and CFD-based velocity assessment are quite similar.

### 8.3.2 Kernel Deconvolution with $Q$-masking: Patient data

For the patient data, we here also present the multiscale analysis. Figure 8.5 shows the analysis results for patient 1 for two different scales. Figure 8.5 indicates that the flow behavior is rather different at different scales.

Figure 8.5 shows that the vortex rotation axis flips from the $z$- to $x-y$- direction at increasing scale. In the cutting planes of the $\sigma = 0.28$ mm image, two local vortex areas are visible. A blank area separates the two vortex areas, which is the result of the masking with the $Q$-criterion. For a larger scale of $\sigma = 1$ mm, only one large vortex region remains.

This means that the global velocity pattern inside the aneurysm is dominated by one large vortical motion having its rotation axis in the $x-y$ direction while locally small vortices with different rotation axes are present. In this case, both at small and large scale, vortices are found in the same position whereas Figure 8.7 illustrates that locally detected vortices for patient 2 and 3 also vary.
Figure 8.6: Aneurysm phantom flow pattern analysis of PC MRI data (top) and CFD data (bottom) in the aneurysm phantom. In the left figures the phantom surface is rendered. The arrows represent the vortex axes. The strength of the vortex is depicted by the length and color of the arrow. In the right figures the 2D visualizations of the velocity (arrows) and vorticity quantification (colored surfaces) are shown. The dark red colors of the surface visualization depict the center and magnitude of the vortex.

in position and rotation axis at the two different scales; it shows that a general (large or small local scale) description of vortex patterns is not enough to fully grasp flow behavior inside an aneurysm because details at different scales may be missed.

The dynamic behavior of the vorticity during the heart cycle is illustrated in Figure 8.8. During the heart cycle, flow changes considerably, which is also illustrated by the change of vortex center position, direction, magnitude and number of vortex centers. The identification of the vortices at different times allows the tracking of these variations and inspection of their evolution. For example, in patient 3 at the beginning of the cardiac cycle (t = 2 in Figure 8.7) small vortices are present rotating around x – y axis whereas at time t = 12 and t = 24 we find completely different patterns with axis of rotation perpendicular to the initial axis of rotation. Please note the difference in magnitude of the vorticity between patients. This may be explained by differences in flow patterns, or flow magnitudes in the afferent arteries.

8.3.3 Time-resolved $S_m$-criterion

The evolution of shear stress using the $S_m$-criterion is illustrated in Figure 8.9. The arrow color plotted according to $|S_m|$ represents shear stress strength; the arrow direction and length reflect the local velocity vector field. This kind of visualization is employed to inspect unstable shear stress regions, which are often associated with aneurysm growth in literature ([24]). In patient 2, the local maximum shows a constant behavior over the heart cycle. In the two other cases, shear stress profiles are dynamically unstable. For example, in patient 1, strong shear components are found at $t = 2$ in the direction of the vessel inflow, which migrate towards more distal locations. In patient
8.4 Discussion

We have presented a method for visualization and analysis of time-resolved 3D flow features in intracranial aneurysms. Kernel deconvolution with $Q$-masking applied at small scales provides an initial impression of the most interesting flow features, whilst vortex center detection at large scales, gives an impression of the global intra-aneurysmal behavior. With this method it is possible to identify regions with high vorticity and shear stress areas on different scales and to follow their evolution during the heart cycle. The method, successfully tested on artificial phantoms and on patient data, proved to be reliable and effective to visualize specific flow characteristics. CFD simulated velocity and PC MRI measured velocity data in the aneurysm phantom agreed well in location and orientation of the vertices. We have shown that these flow patterns evolve over time and are different for different scales, which emphasizes the importance of analysis of intra-aneurysmal scale for the whole heart cycle. Stability of vortex patterns in time, which is another important parameter in risk of rupture assessment, can be scored with the proposed pipeline. Moreover, changes in magnitude and location of shear stress are also detected and may have important relations with aneurysm growth. This algorithm has the potential to quantify vorticity behavior and help understanding aneurysm flow behavior. In current literature [6, 9], pipelines for qualitative aneurysm risk assessment are presented. However, the inner structure of flow at
Figure 8.8: Kernel deconvolution with Q-masking analysis results at different time steps applied to patient 1 (top), 2 (middle) and 3 (bottom) at a scale of 0.28 mm.

different scale is rarely taken into consideration. Furthermore, quantitative methods able to score local vortex stability and shear stress magnitude can be implemented in the algorithm and used in large-scale studies to improve intracranial aneurysmal risk assessment.

In clinical studies, vortex behavior has been associated with rupture status. In near-future studies, the quantified measures as presented here, need to be associated with these qualitative measures such as they are now included in studies that associate intracranial hemodynamics with aneurysm rupture risk. A quantitative approach as presented here may reduce the interobserver variability and potentially increase the predictive value of vortex instability. Since the generation and interpretation of the quantified results still requires quite some effort, future perspectives are to automatize the detection allowing quantification of parameters in large populations. We believe that this is helpful in future clinical treatment decision. However, the agreement of the presented quantitative measurements with qualitative assessments needs to be studied in more detail in future longitudinal studies with larger patient populations.

Vortex detection may appear relatively easy using animations of streamlines or similar visualization. However, the low interobserver agreement associated with vortex classification suggests otherwise. Moreover, especially for smaller scales, the presented algorithm suggested vortex cores that were not observed by the initial visual analysis of the streamlines. Only careful inspection of
the flow vectors in the 2D planes in the detected vortex centers showed that indeed small-scale vortices were present in the image data. Therefore, we believe that the suggested approach in which local maxima of vortex magnitude are detected and subsequent 2D planar visualization of the velocity vectors results in a more detailed and correct description of intra-aneurysmal flow.

The vortex quantification allows for a quantitative comparison of flow fields originating from different modalities. In van Ooij et al. the singular energy of flow characteristics obtained with MR and CFD were compared indicating good agreement in systole, and differences in diastole flow patterns due to low signal to noise ratios (7).

Aneurysm initiation and rupture is the result of vascular wall failure rather than resulting from hemodynamic behavior solely. When the cerebral artery wall has become too weak to resist hemodynamic pressure it distends. Subsequent wall degeneration may lead to impaired endothelial function. Intra-aneurysmal flow conditions may subsequently decellularize and degenerate the arterial wall making it prone to rupture (25).

We should notice that this study suffers from a number of limitations. First, the CFD computations depend on a number of assumptions that may not hold: Newtonian fluid, rigid vessel walls. Furthermore no mesh refinement studies have been performed prior to analyzing the CFD results.
We have presented a multi-scale analysis, but detailed information on the relevance of different vortex scales for aneurysm growth and risk of rupture remains unanswered. Based on current literature, we believe that both small-scale vortices (9, 26–28) and larger-scale vortices (14, 29) have a degenerative biological effect. Here, only two vortex scales were presented. Still, this confirms that there is indeed a scale-dependence of vorticity in the flow patterns. In a subsequent study, the scale selection for maximum agreement with clinical interpretation and rupture status will be addressed. However, this was beyond the scope of the current study. The multi-scale approach may result in a data increase rather than a simplification of the interpretation of the flow data. In future practice, large-scale vortices may be presented initially, after which smaller-scale structures may be studied consequently by decreasing scale with a graphical user interface. However, this approach has not been tested in this study. Our method has been applied for the quantification of intracranial aneurysmal flow. However, it is not limited to this application area. It may potentially quantify flow features in other applications such as intra-ventricular flow (30), flow in jugular veins (31), and aortic root flow patterns (32). However, this was beyond the scope of the current study.

8.5 Conclusion

We have presented a full-fledged scale dependent and dynamic vortex identification and quantification method. This method has been applied to a phantom model and 3 patient-specific flow fields illustrating temporal and scale-dependency of the vortical flow patterns. The quantification of vortices has the potential to be implemented in large-scale clinical studies to associate rupture status with vortex stability, creation, and termination. The scale-dependence of this approach may allow the detection of smaller scale vortices that may be obscured in conventional visualization schemes.

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multi-scale 3D+t intracranial aneurysmal flow vortex detection


