Blood Flow Estimation by Means of Intraoperative Rotational Angiographic System

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Abstract:

We present an algorithm for estimating the blood flow in angiographic image data. In corresponding projective digital subtraction X-ray angiography (2D-DSA) data sets we analyze the correlation between Concentration Time Curves (CTC) of pixels along the vessel centerline. The appropriate spatial information is recovered by applying a 2D-3D registration re-projecting the centerline pixels to the reconstructed 3D X-ray rotation angiography (3D-RA) data of the same object. Ambiguities caused by occluding vessels are resolved by a graph-based approach. Finally, we end up in a framework for the estimation of a real spatial blood flow. This measure is used as boundary condition for blood flow CFD simulations. The algorithm has been tested on phantom data. First plausibility tests of this re-projection method on patient data indicate its ability to also properly function on these data.

Keywords: Blood Flow, X-ray, Angiography, Registration

1 Problem

For an accurate patient-specific blood flow simulation, the cerebral vascular system has to be modeled in its complex structure. This includes the topology of the vessels around the aneurysm as well as the blood flow velocity and propagation. Most of these parameters are highly patient-specific, therefore, we wish to acquire the necessary information from image data of the patient. The 3D morphology of the vessel can be extracted from the CT-like reconstruction of the X-ray rotation angiography (3D-RA) scan, while boundary conditions for blood flow are measured in projective digital subtraction X-ray angiography (2D-DSA). Both image modalities are acquired routinely prior to treatment using one device, i.e. the interventional rotational angiography system.
The measured velocity profiles of the vessel feeding the aneurysm can be used as an inlet boundary condition for CFD computation. Exact boundary conditions are crucial for a high quality numerical simulation.
As digital subtraction X-ray angiography images are projection images, blood flow can only be measured in pixel units per time [px/s]. Hence, velocity information from 2D-DSA has to be fused with morphology from reconstructed 3D X-ray rotation angiography for providing true distance information necessary for accurate CFD simulation. This can be performed by means of 2D-3D registration methods. With this knowledge, we are able to derive the spatial blood flow from the 2D-DSA images by incorporating the morphology of the vessels from 3D-RA. The blood flow propagation in terms of real spatial units [mm] is now available as a boundary condition for CFD simulation.
A review of recovering blood flow velocity from series of projective images can be found in [1]. However, only few methods exist in the field of recovering true blood flow from projective images. A method similar to our approach was published by Schmitt [2]. The method relies also on re-projection of 2D images. However, the basis of the ambiguity solving approach is a symbolic vessel tree. That incorporates additional effort and an additional source of error. The accuracy is unclear as quantitative results are not provided. Methods of 2D-3D registrations have been presented by Liu [3] and Rohlfing [4]. These approaches comprise just the registration of the projection image with a projection computed from the volume data set while the recovery of depth is not included. Generally, 3D information is transformed to 2D information. We need a reciprocal approach as we focus on recovering spatial information from projective pixels.

Fig. 1. Overview of the workflow

2 Methods

2.1 Measuring projective blood flow

We aim to determine the mean 2D pixel blood flow velocity from time-dependent 2D-DSA images. These images can be acquired from arbitrary plane positions by means of modern rotational angiography devices with a sufficiently frame rate of at least 30 frames per second (fps). Blood flow is measured by detection of contrast agent (CA) and its propagation through time. Since injection of the CA strongly disturbs the blood flow propagation, the estimation of the true blood flow velocity by bolus tracking requires a linear correction factor [1]

A 2D-MAX image is produced by computing a maximum intensity projection along the time axis to ensure that vessel pixels are clearly distinguishable from background pixels. A ROI is chosen manually, which contains the feeding vessel to an aneurysm. The flow in the vessel is characterized by measuring the blood flow along its centerline. The centerline is extracted by threshold segmentation of the 2D-MAX image followed by a thinning step that produces a centerline with a width of 1 pixel and 8-cell neighborhood. The centerline extraction is semi-automatic and requires little user-interaction. Distance information along a centerline is generated by tracking a path from the starting point to the end-point.

Once the vessel and its centerline are segmented, projected blood flow velocity can be estimated. There are two major approaches to compute blood flow propagation from angiographic images [1]. Concentration Time curves (CTC) track the bolus propagation by observing the change of pixel intensity while Concentration Distance Curves (CDC) track the front propagation of the bolus. We have chosen the first approach, because we are interested in a mean velocity along the vessel centerline. Due to pulsative behavior of the blood flow, this can be measured integrally more precisely by CTC. Furthermore, CTC take all time frames at all locations into account, while CDC relies on time frames where the bolus propagation is visible.

Since blood flow is assumed to have constant velocity, it can be derived from observing the displacement of the intensity profile of contrast agent along the vessel centerline. Propagation of flow at a position p_i with respect to a position p_0 on the vessel centerline is measured by the delay δt of the two corresponding CTC and the known distance Δs between p_0 and p_i. The velocity is then $v = \Delta s/ \delta t$. The delay is given by the maximum position of the cross correlation of the CTC at position p_0 and the CTC at position p_i. This is measured for all possible pairs of positions.

As the CTC only provides discrete intensity information at each time an image has been acquired, the cross-correlation function is a discrete function as well. For a more accurate determination of the maximum position, we use a 4^{th} order polynomial interpolation scheme around the discrete maximum position to estimate the maximum position in continuous space. This step is important in case of a short centerline, where the expected values of the position of the maximum are small.

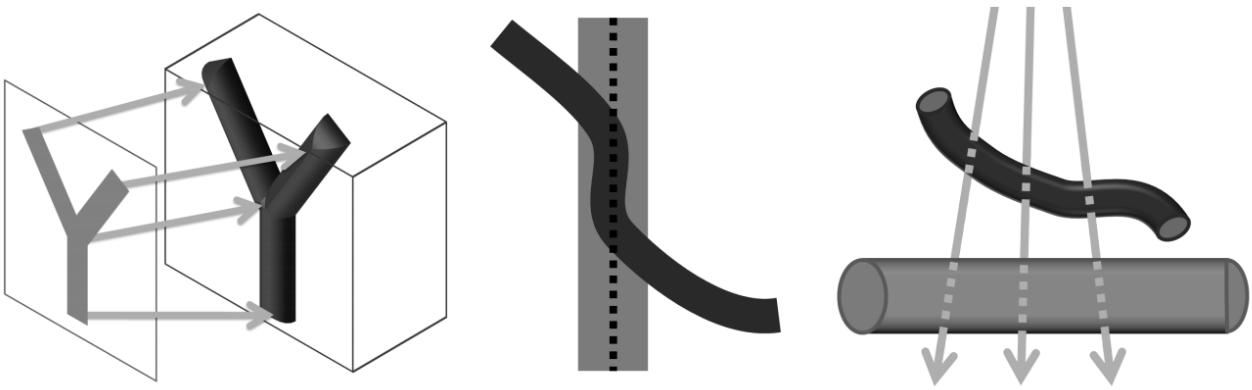
The continuous maximum positions for each centerline pixel provide information about δt and Δs. In order to find a mean blood flow velocity, we perform a linear interpolation of all values. The slope of the interpolation function yields the reciprocal pixel velocity. As indicated before, a linear correction factor c has to be included to estimate the correct blood flow velocity from measured bolus propagation. We estimate the factor experimentally by injecting different volume amounts into the cerebral phantom (Section 3). The undisturbed blood flow is computed by taking advantage of the linear relationship between contrast agent quantity and measured blood flow velocity. The measured blood flow velocity is plotted against the quantity of the injected CA. A linear regression line extrapolates the true value of blood flow that is the value for a quantity of 0 ml/s. The phantom correction factor estimated for the phantom is then transferred to the patient data. As the amount of CA is known, the correction factor can be estimated. However, the correction factor is also dependent on the vessel diameter [1]. We assume that the diameter of the feeding vessels does only vary little. This is the case for vessels in the Circle of Willis, which we in this paper focus on..

2.2 Recover spatial information from projective images

Projective blood flow is measured based on a 2D-DSA image sequence at vessel centerline pixels. For recovering metric information we need to assign 3D world coordinates to every pixel of the 2D centerline. Therefore, a re-projection of 2D-DSA data into 3D-RA volume is required. Spatial alignment of the two data sets is given, since a prior 2D-3D registration presented in [5] provides the transformation parameters.

We employ a ray-shooting approach to backproject the projective information from 2D-DSA to registered 3D vessels extracted from 3D-RA. Ambiguous mappings occur if a ray intersects more than one vessel in the 3D scene. We solve the mapping problem by transforming it into a graph-based problem. An undirected graph is built to describe all possible 3D correspondences of the 2D centerline pixels. All vertices that share a common parent 2D centerline neighbor pixel are connected. Costs, associated to the edges of the graph, are defined by intensity, position and connectivity. An optimal path is computed by applying Dijkstra's algorithm.

Finally, we are able to determine the length of the 3D centerline by measuring the Euclidian distance between the centerline nodes. Hence, velocities in [px/s] as a result of the computation in the 2D-DSA data set can be transferred into flow in [mm/s] or [ml/s], respectively, by incorporating a segmented 3D-RA image.



(a) (b) (c)

Fig. 2. (a) Sketch of the re-projection technique. (b) Illustration of the mapping problem: the centerline of the straight vessel (black dotted line) is disturbed by the bended vessel in the projective view. (c) A lateral view on the same scene. The bended vessel occludes the straight vessel. The re-projection rays (gray arrows) determine 2 candidates for 3D correspondence to 2D vessels.

3 Results

We evaluated our method on phantom as well as on patient data. Two different information provided ground truth to validate our measurements on the phantom: Laser Doppler Velocimetry (LDV) and the total delivery rate of the used pump. In the case of patient data, only plausibility tests could be performed as ground truth information was not available. However, the main focus of this paper is to prove the general functionality of the presented framework.

We used a cerebral vessel silicone phantom that includes three aneurysms (Elastrat H+N-R-A-EV-003). The fluid was pulsatively pumped through the artificial vessels by means of a pump. For the experimental setup and further information about LDV, we refer to [6].

LDV measurements led to a mean flow velocity of 226 mm/s, measured in the investigated. The known delivery rate of the pump was 5.25 ml/s and the mean diameter of the feeding vessel was 5.3 mm. It results in a mean volume flow within the vessel of 229 mm/s. Hence, due to the uncertainties of the given parameters the ground truth differ by approximately 1.3 %.

We measured the mean projective blood flow velocity with 2D-DSA images acquired from 2 different angles. By our method, we measured a blood flow of 1075 px/s for angle 1 and 1092 px/s for angle 2. The centerline had a projective length of 434.8 px and 526.6 px, respectively. The spatial length was 107.6 mm and 98.4 mm. Division of the spatial length by the pixel length yields a total pixel spacing. Multiplying this value by the projective pixel flow, it results in a volume flow of 266 mm/s for the projective data set for angle 1 and 204 mm/s for the projective data set for angle 2. Hence, the deviation was 17.7 % against the LDV measurements and 16.2 % compared with the the pump delivery rate for the first data set. The precision of the flow results for the second data set was 9.7 % and 10.9 %, respectively. For a patient data set, we determined a blood volume flow of 2.21 ml/s in a cerebral vessel with a diameter of 4.6 mm.

As our algorithm is designed for the usage of real patient data, we also performed experiments on five patient data sets. Due to the lack of ground truth, we carried out plausibility tests of our spatial recovery approach (section 2.2). In two bi-plane 2D-DSA data sets (difference of the plane angles is approximately 90°), the projection of a 3D centerline has a different path and length. We used this fact to re-project the manually chosen 2D centerlines that share a common 3D centerline. Hence, the re-projected length of the centerline is ideally the same for both 2D-DSA data sets. We have manually chosen feeding vessels that are defined by a start and end point. Both points are defined by salient images features like bifurcations and aneurysms. Usually, feeding vessels are larger vessels as the probability of aneurysms formation is higher. As measure, we used the deviation on a percentage basis from the length of the spatial recovered 3D centerlines. We measured a deviation between 0.3 % and 6.9 % with a mean deviation of 3.9 %. This is accurate under our assumptions as the 2D centerlines differ quite strong in terms of path length. Additionally, the re-projection is disturbed by close-by vessels and vessels occluding the vessel of interest.

4 Discussion

In order to support physicians in the treatment of intracranial aneurysms the qualitative information on blood flow in the feeding vessels is of high importance.
We presented a method to measure the blood flow velocity in angiographic image data. Projective pixel blood flow velocity was extracted from 2D-DSA by measuring the blood flow at vessel centerline positions. Spatial information was included by incorporating 3D-RA data. A 2D-3D registration and a consecutive re-projection provide the transformation of pixel data to 3D coordinates. A graph-based scheme was introduced to resolve ambiguities caused by occluding vessels.
We tested our algorithm on a cerebral vessel phantom and proved the quality and the functionality of our approach. With respect to our assumptions, we are able to compute the blood flow velocity with good accuracy. Compared to literature, we presented several improvements in different scopes. The projective blood flow propagation is computed by comparing Concentration Time Curves of all vessel centerline pixels rather than taking just a subset of pixels into account. To recover spatial information from projective images, we use a re-projection approach that solves projection ambiguities by estimating an optimal cost based path through a graph that is built by registration knowledge. This is a rather straightforward, but easily extendible method to map positions from a 2D-DSA image to a 3D-RA volume.
The results lead to an improvement in CFD simulations as the inflow blood velocity is not estimated from patient data, but usually given by a uniform distribution according to literature. With our approach, for each phantom or patient a specific boundary condition for the CFD simulation can be applied. This is especially interesting in the case of patient data. However, the evaluation of our results and comparison with other methods is difficult since accurate quantitative measurements are typically not given or, if available, not directly comparable as the experiments and ground truth data differ. As an example, the reported accuracy in [7] is similar to our precision. With respect to our measurements, we expect that a better utilization of the relationship of bi-plane projection images into the process will lead to a more precise estimation of the blood flow velocity.
For the future, we plan to test our algorithm with further patient data. In this context, the transfer of the correction factor to recover true blood flow from measured bolus propagation is subject to further investigation. Additionally, we plan to test the influence of parameters like position and length of the chosen vessel centerline on our algorithm.

5 References

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