

Doppler-based 3D Blood Flow Imaging and Visualization

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Abstract

Blood flow is a very important part of human physiology. In this paper, we present a new method for estimating and visualizing 3D blood flow on-the-fly based on Doppler ultrasound. We add semantic information about the geometry of the blood vessels in order to recreate the actual velocities of the blood. Assuming a laminar flow, the flow direction is related to the general direction of the vessel. Based on the center line of the vessel, we create a vector field representing the direction of the vessel at any given point. The actual flow velocity is then estimated from the Doppler ultrasound signal by back-projecting the velocity in the measured direction, onto the vessel direction. Additionally, we estimate the flux at user-selected cross-sections of the vessel by integrating the velocities over the area of the cross-section.

In order to visualize the flow and the flux, we propose a visualization design based on traced particles colored by the flux. The velocities are visualized by animating particles in the flow field. Further, we propose a novel particle velocity legend as a means for the user to estimate the numerical value of the current velocity. Finally, we perform an evaluation of the technique where the accuracy of the velocity estimation is measured using a 4D MRI dataset as a basis for the ground truth.

CR Categories: J.3 [Computer Applications]: Life and Medical Sciences Biology and Genetics I.3.3 [COMPUTER GRAPHICS]: Picture/Image Generation Viewing algorithms

Keywords: Biomedical and Medical Visualization

1 Introduction

Blood flow assessment using ultrasonography is important in prevention, diagnosis, and monitoring of diseases. There is a broad spectrum of clinical scenarios, where blood flow analysis is significant for patient outcome. One example is the assessment of atherosclerosis for the prevention of thromboembolic events, such as myocardial infarction or cerebral stroke. Information about turbulence and velocity profiles in 3D can be utilized to diagnose and follow-up patients. Another medical scenario is intra-operative 3D blood flow assessment during a transplantation surgery, where blood flow characteristics could aid the surgeon in completing a

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successful procedure. In a post-operative scenario 3D blood flow turbulence could be assessed after, for example, coronary artery bypass graft (CABG) operation, and later follow-up and prevention of atherosclerosis in coronary arteries. Furthermore, blood flow analysis can be used in cancer assessment to monitor the response of treatment through changes over time in angiogenesis [Postema and Gilja 2011] and/or blood flow to the tumor. Furthermore, in pregnancy, changes in the placental blood flow can be monitored in cases of intrauterine growth retardation. Moreover, measurement of flow and perfusion may play an important role also in targeted treatment using ultrasound and microbubbles [Postema and Gilja 2007].

The blood flow quantification, is carried out using various imaging modalities. The most advanced non-invasive imaging method for blood flow velocity measurements is the 4D magnetic-resonance blood-flow imaging (4D MRI). This modality measures true velocities of the blood in 3D, delivers the best imaging quality, and is in daily use for imaging heart and aortic arch blood flow. The 4D MRI is at the same time a very costly procedure, which cannot be performed bedside, and the flow analysis is carried out as postprocessing, disallowing in-situ flow visualization and analysis.

A widely used method for blood flow assessment is ultrasound-based Doppler imaging. This imaging modality can convey blood flow in real time. However only projections of velocity vectors, instead of true velocity vectors, are imaged and visualized. The true velocity is unknown, as only its projection onto the ultrasound beam can be measured by means of the Doppler phenomenon. Therefore, the examiner has to mentally reconstruct the blood flow velocity by considering the angle between the imaged blood vessels and the direction of the ultrasound beam. The more the beam is aligned with the vessel, the more the Doppler measurements represents the true blood flow characteristics. This is, however, often not achievable due to the alignment of the vascular structures.

Recently another modality has been introduced to the clinical arena. It is known as the B-flow technique that visualizes the movement of the blood cells as particles. It provides a good qualitative description of the blood flow velocity, given that the beam direction is aligned with the blood flow. This modality however, does not provide any quantitative measures of velocity, it is only available as 2D, and since it requires high frequency ultrasound it has fairly low penetration, limiting its use to vascular structures located directly beneath the skin.

There are other imaging modalities that can provide some information about the blood flow in situ. The X-ray based digital subtraction angiography (DSA) can reveal occlusions, and contrast-enhanced ultrasound (CEUS) can convey perfusion and angiogenesis. These techniques however, rather than measuring the flow phenomenon directly, provide information about the structure the flow is embedded in. Moreover, DSA and CEUS techniques involve the use of intravenous contrast agents and thus could be considered as being invasive imaging methods.

From the brief review of available imaging modalities it becomes

apparent that there are currently no modalities which provide a satisfactory option for measuring blood flow quantities in-situ over larger areas of a blood vessel non-invasively. 3D Doppler ultrasound is the only modality which has the potential for real-time quantitative blood flow measurements non-invasively, but the estimates of flow information are prone to errors. The true flow direction is missing in 3D Doppler imaging. Assuming laminar flow, this can be estimated by tracing the direction of the vessel. The goal of this project was therefore to develop an imaging and visualization approach that combines the positive properties of 4D MRI and 3D Doppler imaging, which is in short: in-situ 3D blood flow velocity and flux (transport of blood at a given cross-section) quantification.

The main idea of our blood flow reconstruction methodology is based on combination of (a) the assumed flow direction with (b) the implied flow orientation and velocity magnitude. This approach is carried-out as a two-stage process. In the first stage the flow direction is estimated. The fundamental component of vascular blood flow is laminar and our flow model also considers only laminar vascular flow. With this assumption we are able to extract the blood flow direction from the vessel geometry, or its respective skeleton. The second stage estimates the blood flow velocity magnitude and its orientation. This information is obtained from the continuous flow (CF) Doppler measurements, and by backprojecting these onto the assumed flow direction.

Besides the blood flow reconstruction, the second contribution of this paper is a tailor-made visualization design that effectively depicts qualitative and quantitative characteristics of the blood flow dynamics. The third contribution is a preliminary evaluation of selected aspects of the novel imaging and visualization methodology. We perform an in-silico study to investigate the angular certainty ranges and informal evaluation of user satisfaction with the segmentation interaction and the applicability of flow labels for velocity quantification purposes.

2 Related Work

There are two major classes of prior work related to proposed concept on blood velocity imaging from the Doppler data and visualization of the blood flow. One class deals with the challenge of reconstructing blood flow and the second class deals with the problem of how to effectively visualize measured or simulated blood flow phenomenon.

Imaging: Kripfgans et al. proposed a Doppler-based blood flow reconstruction method, known as *surface integration of velocity vectors* (SIVV) [Kripfgans et al. 2006]. This work is estimating the flux quantities, without an a-priori knowledge about the vessel orientation. It is based on the Gauss' theorem, which relates the flux through an area with the divergence of the velocity vectors. Authors acquire the Doppler signal from a vascular structure, where an array-of-beams series constitutes one cross-section plane over the vessel. The cross-section consists of small surface areas, perpendicular to the beam. The Doppler values from this array-of-beams series are multiplied with the small surface area of the cross-section corresponding to each individual Doppler value. The total flux is the sum of these multiplications. Later this technique has been extended by an in-vivo study, taking into account the pulsative arterial flow [Richards et al. 2009]. Both in-vitro and in-vivo studies confirmed a 10% deviation from the gold standard, and thus Doppler-derived flow was considered as a reliable method for estimating flux in blood vessels.

Our approach, in contrast to the SIVV technique, focuses on estimation of true blood velocities, instead of flux at the first place. From

the reconstructed true velocity values we are able to compute the flux, while SIVV does not offer computing blood velocity without prior knowledge of the flow direction. The aim of our research was to provide the examiner qualitative visualization means conveying the blood flow coupled with quantitative flow velocity magnitudes and flux. The SIVV technique can provide only the quantitative flux information.

In ultrasound workstations, Doppler flow estimates can be improved by manually defining the direction of the flow. Hausken et al. demonstrated how this can be used for quantification of gastric emptying and duodenogastric reux stroke volumes [Hausken et al. 2001].

Our reconstruction pipeline is based on the vessel geometry information obtained through a rapid segmentation process. For this purpose we have adopted the fuzzy segmentation technique from Petersch et al. [Petersch et al. 2006] for hypoechoic regions, which is based on a non-linear diffusion technique. This 3D segmentation technique has been adapted for live vessel extraction from a position-tracked 2D ultrasound [Birkeland and Viola 2010]. While such an approach was reported to deliver reasonable results for patients during a breath-hold, it was not robust enough with respect to voluntary and involuntary patient-anatomy movements.

In ultrasound imaging there is a strong need for positioning information, which is robust with respect to various sources of tissue movements. In our pipeline we incorporate recent work where the positioning is based on an image-based registration of 4D ultrasound [Øye et al. 2012]. Having positioning information based on internal tissue information, the breathing will not affect the precision of positioning, unlike other positioning approaches facilitating external positioning hardware.

Visualization: The output of basic Doppler ultrasound imaging is a signed scalar field depicting the velocity of the blood towards or from the ultrasound probe combined with a B-mode image for structural reference. In a typical ultrasound workstation, 2D Doppler is displayed as a colored overlay over the B-mode with a corresponding legend depicting which color correspond to which velocity. 3D Doppler is rendered using direct volume rendering (DVR), blending both the B-mode and the velocities. Still, 3D Doppler ultrasound data is very dense and it is challenging to combine both structural and flow information in a meaningful manner. However, Petersch and Hönigmann developed a new method for blending 3D B-mode data with 3D Doppler data [Petersch and Hönigmann 2007]. They demonstrated a blending technique using a one level composite rendering approach. They combine silhouette rendering for the B-Mode and a mix of Phong shaded DVR and silhouette rendering on color Doppler. Jones et al. discuss several approaches to explore and visualize 4D Doppler data [Jones et al. 2003]. They apply a surface fitting technique on the Doppler data based on YCbCr color scheme values. This improves the separation between Doppler data and B-mode data. Using multi-planar slice rendering into a DVR scene, the details can be observed in the slice while a semi-transparent DVR provides the context.

While Doppler ultrasound visualization has the challenge of combining two scalar volumes, 4D magnetic resonance imaging (MRI) can provide accurate measurements of the *real* velocities [Potchen et al. 1993]. This introduced new complexity to visualizing blood flow. Van Pelt et al. demonstrated different illustrative techniques for exploring and visualizing blood flow dynamics based on 4D MRI [van Pelt et al. 2011a]. They evaluated a set of proposed visualization techniques using integral lines and arrows seeded at cross-sections. Later van Pelt et al. presented a technique, using particles as a means for depicting the flow, which was evaluated to enhance the perception of the blood flow recirculation [van Pelt

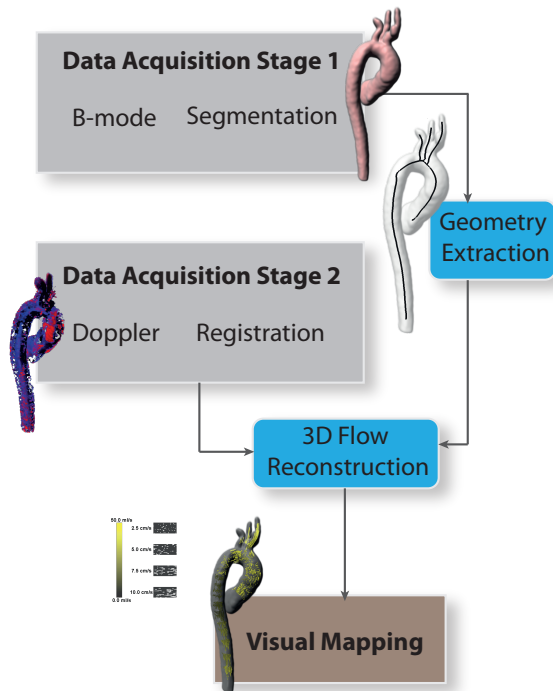


Figure 1: An overview of our method. Stage 1: Firstly, we create a segmentation mask of the blood vessels using B-mode ultrasound. Secondly, we acquire geometry information by extracting vessel center-line. Stage 2: we register Doppler ultrasound with previously segmented blood vessels. Secondly, combine the ultrasound information with the geometry information to reconstruct blood flow. Finally, we display reconstructed blood flow using illustrative flow rendering. Images show in-silico examples generated from 4D MRI data of the aortic arch.

et al. 2011b]. To compensate for the high density of information van Pelt et al. presented a method for spatio-temporal hierarchical clustering [van Pelt et al. 2012], relieving clutter from the image by visualizing the clusters as path arrows.

Computational fluid dynamics (CFD) simulation of blood flow can also provide 3D or 4D flow data. Gasteiger et al. combined illustrative surface rendering and flow visualization for analysing cerebral aneurysms [Gasteiger et al. 2010]. Recently, Gasteiger et al. presented the *flow lens* metaphor, a focus-and-context based approach for exploration of both 3D and 4D flow datasets from CFD and phase-contrast MRI datasets of aneurysms [Gasteiger et al. 2011].

The review above of blood flow visualization methods was aimed to provide a short overview on the major trends in the medical-oriented flow visualization research field. A comprehensive survey of the state-of-the-art blood flow visualization techniques is provided in the referred report [Vilanova et al. 2012].

3 Methodology

There are several stages of reconstruction required before we can visualize 3D blood flow using color Doppler ultrasound. The general pipeline of our approach is depicted in Figure 1. In the first

stage, we start out with creating a segmentation mask of the blood vessels which are of interest. After a suitable segmentation has been acquired, we extract geometry information using a center-line extraction technique. From the geometry information, we generate a vector field, where each vector represents the blood vessel direction at the current location. In the second stage, we start by acquiring 3D Doppler ultrasound. In order to correctly include the Doppler ultrasound into our reconstruction technique, we co-register the Doppler ultrasound with our vessel segmentation mask, using image-based tracking [Øye et al. 2012]. The co-registered Doppler signal is then combined with the vector field, representing the vessel directions. Assuming a laminar flow, we define the flow direction as the direction of the vessels. We reconstruct the 3D blood flow by back-projecting the Doppler information onto the assumed flow direction, generating an unsteady flow field live during an ultrasound examination. Finally, we have designed a tailored visualization for this newly acquired data focused on depicting local velocity and total flow throughput at user-defined cross-sections. The following sections describe the different stages in our pipeline.

3.1 Vessel Geometry Extraction

The geometry of the blood vessels is essential for reconstructing the 3D blood flow. While there exist techniques to register pre-segmented vessels from other modalities, such as CT [Papenberg et al. 2008], our system does only rely on ultrasound data. Not depending on a multi-modal approach, alleviates the need for a more time-consuming and costly medical procedure.

To rapidly and robustly extract blood vessels from ultrasound, we have adopted Petersch et al.’s 3D soft segmentation approach [Petersch et al. 2006]. The 3D soft segmentation technique uses a region growing method on a new distance function, which combines the geometric distance to the seeding point and the difference in intensity at a given point and at the seeding point.

The spatial extent of a 3D ultrasound scanning sector is relatively small compared to other modalities. Blood vessels might extend further than what is captured by a single 3D ultrasound sector. In addition, since ultrasound data has a low signal-to-noise ratio and is heavily affected by inconsistent data values, a global segmentation approach is prone to errors. In order to segment larger structures and interactively select which blood vessels to segment live during an examination, we have tailored our method to take into consideration the expertise of the user, allowing the user to locally segment areas, which is suitable through visual feedback. Figure 2 depicts the size of a segmented vessel using our technique, compared to the size of a 3D ultrasound scanning sector.

In our method, the user applies Petersch et al.’s segmentation method to data acquired during a 3D ultrasound scan. A problem is to combine the segmentation from one time step with the segmentation from the next one. Performing this manually would be very tedious and inefficient. Instead we create a compound volume over the entire area of interest, facilitating the image based tracking [Øye et al. 2012]. Consequently, we are able to determine the location of the ultrasound probe relative to the compound volume.

The compound volume is generated by automatically stitching together several ultrasound sectors from a sweep-scan over a larger area. The composite volume can then work as a global positioning reference for the segmentation process. During the scan, the segmentation from each time frame is directly shown in a 3D view, allowing the user to evaluate the current segment to whether or not it is a desired section of the blood vessel. If the current segment is deemed valid by the user, it is stored in a volume co-registered

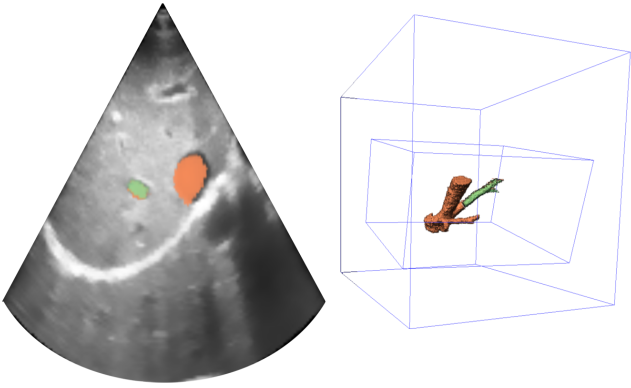


Figure 2: During the segmentation process, the user can observe the results both in a 2D slice view and a 3D view. The current extracted segment of a hepatic vein is shown in green and the stored segmentation mask is shown in orange.

with the composite volume. The user continues to iterate over this process until a sufficient segmentation mask is acquired.

After a suitable segmentation mask of the vessels has been acquired, we can extract information about the direction of the vessels. Our system assumes that the main flow in blood vessels is laminar, which means the flow vectors in a given cross section are parallel and follow the direction of the vessels. To determine the flow direction, we then need the direction of the vessel itself. The general direction of the vessel corresponds to the direction of its centerline. To robustly extract the center line from ultrasound based data, we require a technique which is not sensitive to noise. We implemented the centerline extraction technique based on level-sets presented by Hassouna et al. [Hassouna and Farag 2005].

The centerline extraction technique works as follows. First a single centerline point is extracted automatically as the point with the highest distance to the surface. From the starting point a fast wave is propagated throughout the volume. Speed of the front of the wave at a given point is defined as:

$$F(\mathbf{x}) = e^{\alpha D(\mathbf{x})}, \alpha \geq 0, \quad (1)$$

where $D(\mathbf{x})$ is the distance to the surface from a point \mathbf{x} and the parameter α is user defined. We followed Hassouna et al.'s advice which states that using a pre-set of $\alpha = 25$ provides sufficiently robust results. From Equation 1, we get a cost function,

$$U(\mathbf{x}) = e^{-\alpha D(\mathbf{x})}, \alpha \geq 0, \quad (2)$$

where the minimal cost path between two central points is a centerline. To extract the center-line, we start with the seeding-point and calculate the cost $D(\mathbf{x})$ at each point as the wave propagates. We can then back trace from a topological significant local maxima in the cost function, along the gradient of the cost-function to the starting seeding point, creating a path representing the final centerline.

3.2 Flow Reconstruction

Doppler ultrasound is primarily examined as a live stream. In order to achieve live update of the blood flow reconstruction, we generate a vector field where each voxel contains the current vessel direction. Along with the Doppler signal, there is a separate corresponding B-mode image. This enables us to co-register the Doppler ultrasound

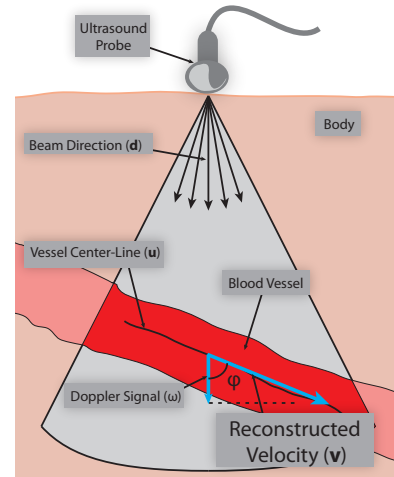


Figure 3: Reconstructing the actual velocity of the flow by projecting the measured velocity from the Doppler ultrasound onto the vessel direction.

with the vessel directions by applying the same registration technique used in the segmentation approach.

Doppler ultrasound contains a large amount of noise from movement in surrounding tissue. Before we start the reconstruction we mask out the noise by sampling the the Doppler signal only within the segmented vessel. Doppler shifts are measured relative towards or from the *viewer*. In color Doppler ultrasound, this means the measured direction \mathbf{d} at given point, is the normalized vector from the probe position to that point. The blood flow is denoted as a unit vector \mathbf{u} , which we have estimated to be the direction of the vessel at a given cross-section. If the Doppler ultrasound outputs a value, ω , we can reconstruct the blood flow velocity, \mathbf{v} , using the following equation:

$$\mathbf{v} = \frac{\mathbf{u}}{|\mathbf{u} \cdot \mathbf{d}|} \cdot \omega, \quad (3)$$

as illustrated in Figure 3.

The Doppler ultrasound measurements become more inaccurate the more the blood flow direction becomes orthogonal to the beam direction. Similarly, as we can see in Equation 3, the flow reconstruction gets more prone to numerical errors as φ approaches 90° , where $\cos \varphi = \mathbf{u} \cdot \mathbf{d}$.

Having reconstructed the flow velocity, we can calculate more aspects of the blood flow. The flux is the volume of flow moving through a cross-section of the blood vessel over time. Since we have the blood vessel already defined, as well as the 3D flow velocities, we estimate the flux, F , by integrating over the area of the cross section, A , using the following equation:

$$F = \int^A \mathbf{v} \approx \sum_i \mathbf{v}_i \quad (4)$$

where i is a voxel in the cross-section. The cross-section is defined by inserting plane orthogonal to the center-line. We then sum up the velocities from the samples along the given plane, similarly to the SIVV technique.

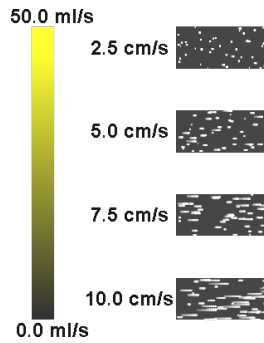


Figure 4: The different legends used for encoding both volume flow and flow-velocity. The users can relate the motion of the particles in the legend to the motion of the particles in the final rendering.

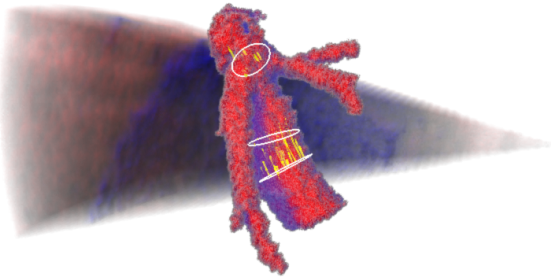


Figure 5: A semi-transparent rendering of the current 3D ultrasound cone allows the user to estimate the angle between the probe and the vessel of interest.

3.3 Visualization

The data generated from the two acquisition stages and flow reconstruction presents the challenge of visualizing multiple aspects of flow and the uncertainty of the data, in a meaningful manner. From the first data acquisition stage, we obtain pre-segmented vessels and a compound volume. Then we generate a separate volume containing 3D vectors, representing the direction of the vessels. In the second data acquisition stage, we obtain a live stream of 3D Doppler ultrasound. The Doppler data registered with the vessel directions provide us with unsteady flow data. While the direction of the vessel is constant for each position in the vessel in our model (we abstract from pulsative behaviour of the artery walls close to the heart), the orientation of the flow vector and its length is updated according to the Doppler data, making the flow unsteady. In addition, uncertainty information is updated along the centerline, when the ultrasound probe is moved.

We examined different types of flow visualization mappings, in order to find out which would be suitable for the multiple aspects of our input data. As the flow directions are constant, performing feature analysis, such as vortex detection in a laminar flow would be meaningless. Since we are focused on displaying the velocities and not how the flow evolves over time, methods such as line integral convolution, path lines/surfaces, or streak lines/surfaces are not suitable as they do not depict the current velocity. For a given point in the vessel, the velocity can either be in the direction of the main flow or opposite if the point is in a backwash area. For this reason time-lines and time-surfaces, which connect particles seeded from cross-sections, would be affected by backwash along the vessel-walls, resulting in very skewed lines or surfaces, and would be difficult to comprehend. Texture advection depicts velocity, but is more

suitable to depict the mixture of the flow, which is not present in laminar flow. This reasoning left particle-rendering as the most suitable means for visual representation of the reconstructed 3D blood flow.

We consider the blood velocity and the flux as the two main properties in blood flow imaging. Therefore we have chosen to use both moving particles and color to depict the two properties simultaneously. In order to get a meaningful interpretation of the flow, we must control the amount of seeded points. To hinder cluttering by an over-abundance of particles, we only seed out particles at user selected areas. The user can simply select an area along the center-line and particles are seeded randomly in the orthogonal cross-section. The motion of the particles depicts the velocities from the cross-section. To prevent perception of the particles from one seeding location to interfere with particles from another, we give each particle a short life time. To increase the spatial understanding of the seeding planes, we insert a circle at the cross-section. The circle helps the user to understand not only the position, but the orientation of the plane provides a circular indicatrix of the vessel direction. Recent studies have shown a systematic distortion of speed perception of moving particles [Birkeland et al. 2013]. They provide a compensation model, which adjusts the velocities in order for the viewer to get a better estimate of the speed encoded in the underlying data. We include this compensation model in our particle animation scheme. Finally, the flux from the seeding cross section is color coded on the particle.

Turbulent flow can occur in blood vessels and this contradicts the assumption of laminar flow. In this case the regions with turbulence will appear as regions where many particles are moving in opposite directions without a distinct pattern, such as a back wash region. In this case it is also important to show the original Doppler signal. We have incorporated a slice viewer which shows a slice of the Doppler signal at the current position of the probes position along the center-line. This enables the user to see the original data at desired positions for validation purposes.

Similarly to color coding, velocity encoding requires a means to estimate the numerical value of the particles in the scene. For this we propose to use a novel visual metaphor, a velocity legend. The velocity legend contains a discrete set of numerical flow values, where each value has a small *flow sample* related to it. Figure 4 shows an example of the velocity legend, where we can see four discrete velocities and the corresponding particle motion.

Uncertainty of the data is another characteristic which is important to communicate to the user. When visualizing data, it can be crucial to inform the user about to what degree she can trust the information in the final image. The reconstructed blood flow is based on a simplified flow model compared to using complex simulation, such as computational fluid dynamics. Opacity is often used as a means to convey uncertainty. However, color is already used to depict flux. An ultrasound examiner is trained to set the angle between the probe and the blood vessels to be not exceeding 60° . Adding the current ultrasound sector as an overlay around the blood vessel, as in Figure 5, the user can estimate the angle between the vessel and the ultrasound probe. Thus, the user can determine how reliable the measurements are.

4 Results

We have implemented the prototype in the VolumeShop framework [Bruckner and Gröller 2005]. The prototype was tested on a Windows 7 system, running a Intel Core i7 3 GHz CPU with a GeForce GTX 680 graphics card. 3D B-mode and color Doppler

ultrasound were acquired using a GE Vingmed Vivid E9 scanner, using a 4V-D ultrasound probe [GE Vingmed 2008].

As a demonstrational case, we have acquired color Doppler measurements from two healthy volunteers. The subject of analysis was the inferior vena cava and the connecting hepatic veins bringing low oxygenated blood back to the heart. These vascularities are frequently investigated for blood velocities and flux, in situations of portal hypertension (post-hepatic) [Mittal et al. 2011]. From a B-mode ultrasound data stream we have segmented the inferior vena cava and the hepatic veins. The resulting segmentation and the extracted centerline can be seen in Figure 6. The segmentation process took after a training period, four minutes. The examiner then swept over the inferior vena cava with 3D color Doppler ultrasound. The velocities are reconstructed in real-time at user selected cross sections seeding particles into the newly acquired flow field. In Figure 7, we show the traced particles from two cross-sections. In Figure 8, images of the inferior vena cava from a different patient are shown.

5 Evaluation

When new data is reconstructed based on a limited amount information, we need an evaluation of the technique to determine its usefulness. We have addressed two aspects: accuracy of the flow reconstruction and user satisfaction of the technique as such. For the accuracy, we compare our results with the actual flow and for the user satisfaction, we evaluate subjectively, how easy users find the implemented prototype to operate.

5.1 Accuracy

To compare the difference between the reconstructed flow and the actual flow, we need a way to measure the *ground truth*. In order to measure the accuracy in our 3D flow reconstruction, we wish to remove noise from tissue movement and probe-movement as much as possible. For this reason, we base our accuracy measurement on an in-silico phantom constructed from the flow measured by 4D MRI scans. We have acquired a 4D MRI flow dataset with a corresponding segmentation mask of the aortic arch. The Doppler signal is synthetically generated as the component vector from a predefined virtual probe position. In this way, we can create artificial Doppler signal from multiple directions to compare how the accuracy compares to the angle between the ultrasound-beam direction and the vessel direction. In Figure 9, rendering of the 4D MRI dataset are shown comparing reconstructed flow (b) with real flow (c).

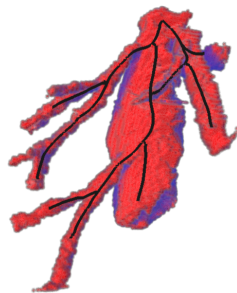


Figure 6: Segmentation mask and centerline of the inferior vena cava with hepatic branches including an aberrant vessel entering below. The vessels were segmented using our approach in about four minutes.

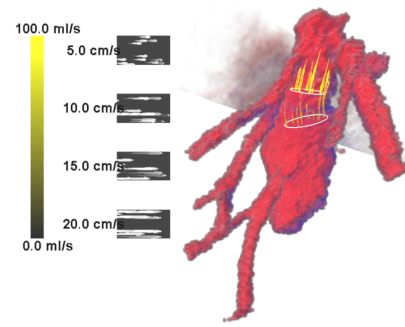


Figure 7: Blood flow reconstructed in the inferior vena cava.

We extract flux estimates from both the recorded 4D MRI blood flow from one time-step, with the corresponding estimated generated by our reconstruction method. Samples are extracted from uniformly distributed cross-sections along the vessel center-line. In total we extracted 1344 samples using four different simulated probe-positions, getting an average estimation of 91% of actual flow. We assume that the error increases as the angle between the ultrasound beam-direction and the flow direction approaches 90° . In Figure 10, we collected the error into bins of 2.5° intervals and plotted the mean and standard deviation of our results. From this graph we can see that the precision of our estimated flow is severely lowered when the angle between the beam direction and vessel direction exceeds 55° . Our method tends to slightly underestimate at degrees lower than 55° , but overestimates when the angle increases. We can assume this overestimation causes bias in our calculation of the total average accuracy. If we look at the average below 55° , we get an accuracy of 69%.

While the simulated Doppler signal does not contain any noise, as Doppler ultrasound would, the flow in the aortic arch is much more turbulent compared to flow in liver vessels due to lower blood velocities. The high turbulence will cause problems when we are assuming a laminar flow, lowering the accuracy. This would indicate a more robust reconstruction is achieved in vessels, such as the inferior vena cava. With these results from the in-silico experiment, we can conclude that flow estimation is possible in laminar-flow dominated veins. However, Doppler ultrasound acquisition is also affected by an error and further investigation is required determine the actual error in-vivo.

5.2 User Satisfaction

During the segmentation procedure, we asked our medical partners to evaluate the workflow of the segmentation process. In general, it was found to be a quick and robust tool for vessel segmentation compared to other segmentation techniques based on level-sets or manual segmentation, our segmentation approach makes it possible for a novice user to segment actual vessel trees within an average of 7-10 minutes. Aspects such as a live updated 3D view of the current segment as well as the larger combined segmentation, which gave direct view of the segmentation progress, was much appreciated. Testing proved that it was difficult to extract smaller vessels due to lack of a *zooming* feature, which can be important for microvascular perfusion analysis. In certain areas, the data values for the blood vessels were too similar to the data values in the surrounding tissue. In these cases, our system was experiencing difficulties differentiating vessels from other tissue. In such a case, features such as manual editing on the 2D slice as well as directly in 3D view were noted as missing.

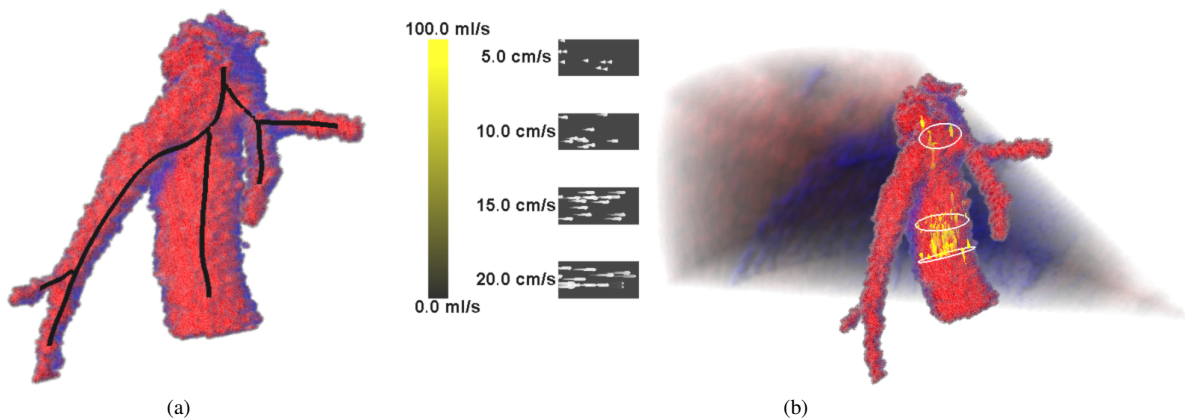


Figure 8: Blood flow reconstructed in the inferior vena cava.

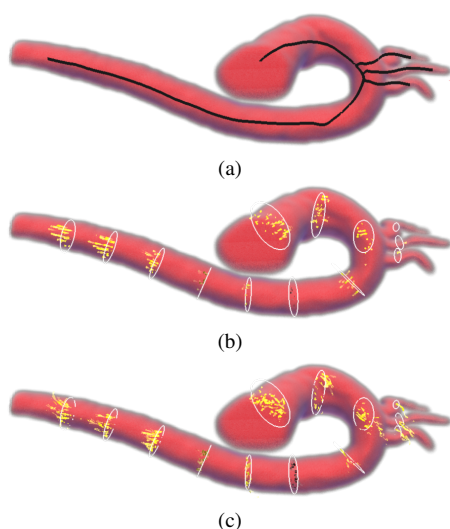


Figure 9: Renderings from our in-silico experimental set-up. Starting with the segmentation mask of the aortic arch, we generate the centerline (a). Images (b) and (c) show our visualization technique applied to the reconstructed velocities and the velocities from a 4D MRI scan.

For the flow reconstruction mapping, our medical partners stated that the reconstruction method showed great potential for the evaluation of degree of stenosis. Also, stent and graft patency are two interesting indications for this method to be further explored with high probability of usefulness. Further testing would be required for the performance of the velocity legend as a means for estimating velocity in a 3D environment.

6 Conclusion

In this paper, we have presented a new method for reconstructing 3D blood flow based on 3D B-mode and 3D color Doppler ultrasound. By segmenting blood vessels from B-mode ultrasound, we anticipate the direction of blood vessels as the direction of the corresponding centerline. In our reconstruction model, we assume that blood flow through vessels is in general laminar, and defines the 3D flow direction as the direction of the vessel. Since the Doppler

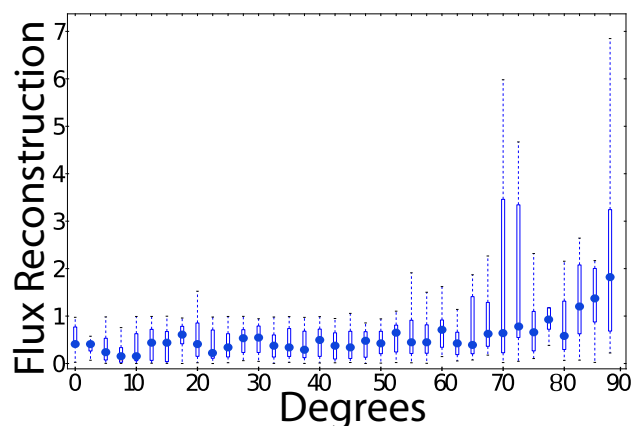


Figure 10: Box-plot of the average estimation in percent compared to the angle between the ultrasound beam direction and the blood flow direction, based on an in-silico experiment from 4D MRI data. Each box show the distribution of the estimation for the samples grouped in 2.5 degree intervals. When the angle between the beam direction and the vessel direction approaches 90° , the error increases significantly.

measurements are only relative to the ultrasound probe position, we back project the data onto the 3D flow directions. Finally, we have proposed a visualization design, tailored for the data generated from our reconstruction technique.

We have performed an evaluation of the accuracy of our reconstruction using 4D MRI data of the aortic arch, by simulating the Doppler signal and using our technique to reconstruct the real velocity. The reconstructed data was then compared to the *ground truth* from the 4D MRI dataset, by comparing the flux at cross-sections along the center-line. We have found that our technique can provide a good estimation of the actual flux. However, the accuracy is highly dependent on the orthogonality between the ultrasound beam direction and the vessel direction. While our accuracy measurement is under ideal conditions, more testing is required to see the performance on *real* ultrasound data. While it is difficult to measure the *real* blood flow non-invasively, future work can include manual blood flow estimation, compared to our method.

Based on our in-silico experiments, we can state that a streamlined implementation of our technique can improve the usability of 3D

color Doppler ultrasound for 3D blood flow estimation.

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