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On the Evaluation of a *Semi-Automatic Vortex Flow Classification in 4D PC-MRI Data of the Aorta*

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Abstract

*In this paper, we report on our experiences that we made during our contributions in the field of the visualization of flow characteristics. Mainly, we focused on the vortex flow classification in 4D PC-MRI as current medical studies assume a strong correlation between cardiovascular diseases and blood flow patterns such as vortices. For further analysis, medical experts are asked to manually extract and classify such vortices according to specific properties. We presented and evaluated techniques that enable a fast and robust vortex classification [MLK*16, MKP*16] that supports medical experts. The main focus in this paper is a report that describes our conversations with the domain experts. The dialog was the fundament that gave us the direction of what the experts need. We derived several requirements that should be fulfilled by our tool. From this, we developed a prototype that supports the experts. Finally, we describe the evaluation of our framework and discuss currently limitations.*

Categories and Subject Descriptors (according to ACM CCS): I.4.9 [Computer Graphics]: Image Processing and Computer Vision—Applications

1. Introduction

Cardiovascular diseases (CVDs) represent the world's leading cause of death [MPN11]. Medical researchers are interested in better understanding the causes of their initiation and evolution. They report on the importance to consider many different variables to judge a patient's situation. Besides the vessel morphology and wall motion, the initiation and evolution of CVDs depends strongly on the blood flow characteristics.

The needed information about the patient-specific hemodynamics can be non-invasively acquired by four-dimensional phase-contrast magnetic resonance imaging (4D PC-MRI) [DBB*15]. 4D PC-MRI data describe time-resolved, 3D blood flow information that represent one full heartbeat consisting of systole and diastole. A qualitative data analysis enables the visualization of vortices that are considered as an indicator of pathologies [HHM*10, HWS*12, MBS*15]. To investigate the influence of vortices on CVDs, medical studies with homogeneous patient collectives are performed. The vortex occurrences are counted and classified according to specific characteristics [GMH*12, HMW*07]. Healthy persons exhibit only a slight systolic helix in the aortic arch, which is considered as physiological [KYM*93]. CVDs lead to altered vessel geometries that increase the probability of emerging vortex flow patterns. For example, patients with a bicuspid aortic valve (AV), where two of the three leaflets are fused, show strong correlations to helical flow in the ascending aorta during systole [HHM*10, MBS*15]. In addition, vortex flow close to the vessel wall is associated with higher shear forces [GBvO*15, vOPP*16], that increase the risk of aneurysm development [BSK*14]. Further understanding this mutual influence of hemodynamics and vessel morphology can support treatment decision-making and the corresponding risk assessment. However, the classification of vortices is a challenging and unstandardized process. Therefore, we present an Aortic Vortex Classification (AVOCLA) that allows to classify vortices in the human aorta semi-automatically. Our approach was developed in collaboration with two domain experts: a radiologist specialized in cardiac imaging with four years of work experience and an expert specialized in the visualization of 4D PC-MRI data with three years of work experience.

2. From Manuel to Semi-Automatic Vortex Classification

The following description is based on [MKP*16].

Manuel Classification. For developing an improved vortex classification, we had to analyze the previous classification approach. Our medical expert stated that the vortex analysis is manually performed until now. Therefore, blood flow-representing path lines are depicted within the vessel surface and common flow visualization techniques such as illumination and particle animations are provided. Moreover, we investigated and discussed widely used classification characteristics and prepared the following list:

- The *shape* refers to the extent of a vortex. Elongated vortices are

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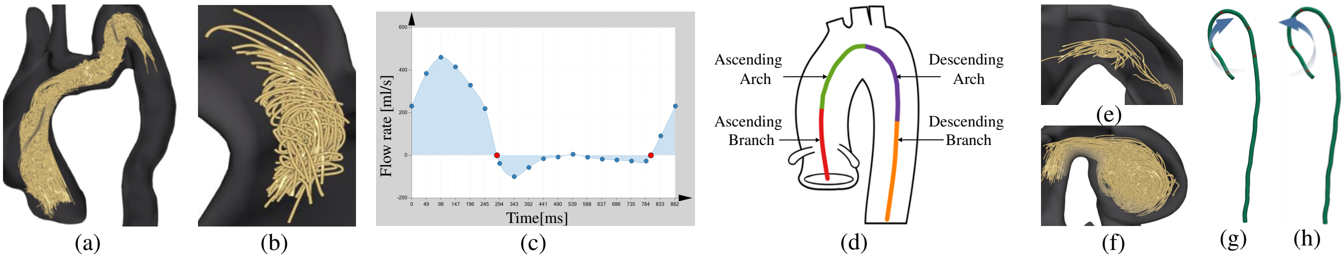

Figure 1: *Vortex classification criteria. The shape is divided into helix (a) and vortex (b). The flow curve (c) is used to determine the temporal behavior. For the spatial classification, four aortic sections (d) are distinguished. The size is divided into minor (e) and pronounced (f) flow and the RD is distinguished into right- (g) and left-handed (h) [MKP*16].*

called helix (Fig. 1 (a)), whereas rather compressed structures are called vortex (Fig. 1 (b)).
- The *time of occurrence* in the cardiac cycle is differentiated according to systole and/or diastole (Fig. 1 (c)).
- The *vessel section* locates a flow pattern to belong to the ascending aorta, aortic arch and descending aorta (Fig. 1 (d)).
- The *size* is divided into minor and pronounced, depending on whether fewer (Fig. 1 (e)) or more (Fig. 1 (f)) than 50 % of the vessel diameter is occupied by the vortex.
- The *rotation direction* (RD) is divided into right- (Fig. 1 (g)) and left-handed (Fig. 1 (h)) with the centerline as a reference.

The vortex properties are determined in a binary manner, except the vessel section. However, our medical expert stated that these binary classifications are often not sufficient to describe the vortex behavior. Visual clutter and occlusions prohibit a more detailed assessment. In summary, the manual classification is described as a time-consuming, subjective and error-prone process with a high inter-observer variability. Our medical expert stated that especially small vortices are easily overlooked. In addition, the analysis of vortices with a similar spatio-temporal behavior is very challenging based on a visual assessment. Our experts emphasized, that a comparability of different datasets is the basic requirement to uncover correlations between vortex flow and certain CVDs. This requires an objective classification according to clearly defined criteria.

Vortex Clustering. To enable a computer-based classification of individual vortices, we had to define vortex entities. Therefore, the vortex-representing path lines should be separated from the laminar flow that is not relevant for the vortex classification. For the extraction of vortex flow, we used the semi-automatic method by Köhler et al. [KGP*13] based on *line predicates*. Afterwards, we used three well-established clustering techniques to separate vortices according to a measure of dissimilarity [MLK*16]. The clustering enables to determine the vortex number and provides a reasonable cluster visualization. We investigated an agglomerative hierarchical, a density-based and a spectral clustering technique, applied to healthy and pathological 4D PC-MRI datasets. The clustering results were compared qualitatively to manually identified clusters of our domain experts. The first approach has been determined to produce the most reliable results. Moreover, our experts appreciated the cluster hierarchy that enables a fast analysis of different cluster numbers. In addition, we provided a merging of different clusters to correct the automatic clustering results, which enables the incorporation of expert knowledge. Thus, the expert has control over the results and is able to handle anatomical diversities such as various vortex numbers and sizes.

AVOCLA. Based on the clustered vortices, we were able to design the computer-based vortex classification. Such a classification need to fulfill several requirements that we defined in consultations with our domain experts. They commented that the classification is required to be performed automatically. However, due to the enormous anatomic diversity, the automatically calculated results will not always be correct. Thus, the experts should be able to manually correct the results. Moreover, the calculated vortex properties should reflect and extend the binary expert classifications according to minor and pronounced flow or helix and vortex. Besides a tabular representation, the experts wanted an adequate visualization of the classification results in order to verify and interpret them better. They commented that an occlusion-free depiction of the spatio-temporal vortex behavior would be very helpful. Therefore, we need a visualization that improves the exploration of the vortex properties.

Based on these requirements, we implemented the semi-automatic vortex classification AVOCLA [MKP*16]. For each clustered vortex, the five characteristics are calculated automatically. However, the expert can manually change the results to correct possible wrong classifications. For the visual representation of the classification results, we chose a 2D plot and a 3D glyph-based visualization, see Fig. 2. The 2D plot allows an occlusion-free depiction of the spatio-temporal vortex behavior without any interaction. Therefore, the temporal component of each path line point is mapped to the angle, whereas the corresponding vessel section is mapped to the radius. The 3D glyph-based representation indicates the vortex size and RD. Therefore, we determined the surface that envelops the vortex, whereupon both properties are mapped.

3. Evaluation

The evaluation of AVOCLA is based on 15 datasets: 2 healthy volunteers with a slight physiologic helix in the aortic arch during systole and 13 patients with different CVDs. Each patient has prominent vortex flow in different parts of the aorta. We performed a qualitative comparison of AVOCLA's results against a manually generated ground truth of our collaborating experts. They determined manually the number of vortex clusters and their characteristics. Therefore, a standard 3D path line depiction embedded in the vessel surface was used and standard flow visualization techniques were provided, such as animation. The 15 used datasets contain a total of 30 vortices. The agglomerative hierarchical clustering [MLK*16] could cluster all datasets correctly according to the manual expert clustering.

Moreover, we conducted a user study with 12 probands, one physician and 11 researchers with background in medical visualization, where our vortex visualizations were compared to the standard 3D path line view (PV). The goal of the user study was to assess the capabilities of our 2D and 3D visualization for expressing AVOCLA's results. The subjects were asked to determine the vortex belonging vessel sections, cardiac phase, RD and size for different datasets. In the following, we describe the main results and findings of the expert evaluation and the user study for each of the five characteristics.

Vortex Shape. According to the shape determination, the binary classification in helix or vortex is not always appropriate because in most cases vortices take on an intermediate shape of both. Thus, our experts also distinguished the intermediate shape. To make the assessment of intermediate shapes more objective, AVOCLA calculates the percentage of helical and vortical flow. The method determined the shape correctly for all vortices. Vortices and helices showed clear differences in their percentage, whereas intermediate shapes had very similar values. Our experts mentioned that the percentage calculation enables an objective description of the vortex shape, which is often not possible based on a visual assessment. However, they commented that our vortex visualizations should more clearly represent the calculated shape, which is currently only indirectly depicted by the extent of the 3D glyph.

Temporal Occurrence. For the classification of the temporal occurrence, AVOCLA calculated the percentage of systolic and diastolic flow. In all cases, the calculated percentage represent the manual classifications. Systolic vortices contain high systolic percentage (> 90 %), whereas vortices in both phases exhibit more similar flow components with a maximum of 68 % systolic and a minimum of 32 % diastolic flow. Moreover, the manual determination was much more time-consuming, because the experts had to repeat the path line animation several times. In addition, all participants of the user study classified the vortices correctly using the 2D plot and described the determination as very simple. In contrast, using the PV two wrong classifications were given and the probands stated that this task is more difficult based on the PV, because of the necessary cluster deselection to observe spatio-temporal vortices individually.

Vessel Sections. The automatic division of the aorta into the four sections correlated in 10 datasets with the manual subdivision, whereas five cases had to be manually corrected. In this cases, a coarctation of the aortic arch led to a strong vessel deformation, so that the automatic division failed. The subsequent determination of the vascular sections conformed with the ground truth for all vortices. However, the experts perceived the manual corrections not as disturbing. The ability to contribute expertise by simple interaction techniques was described as entirely desirable and useful. Moreover, similar to the temporal behavior, all probands of the user study determined the correct vessel section for all shown vortices using the 2D plot. The plot was perceived as very simple and the subjects were certain with their assessments. Based on the PV, the subjects had problems if the vortices are located in more than one section. To see the aortic sections on the centerline, the participants had to deselect clusters, which complicates the task. Furthermore, single outlier path lines, that rise into adjacent sections increase the difficulty of the task and lead to a reduced certainty.

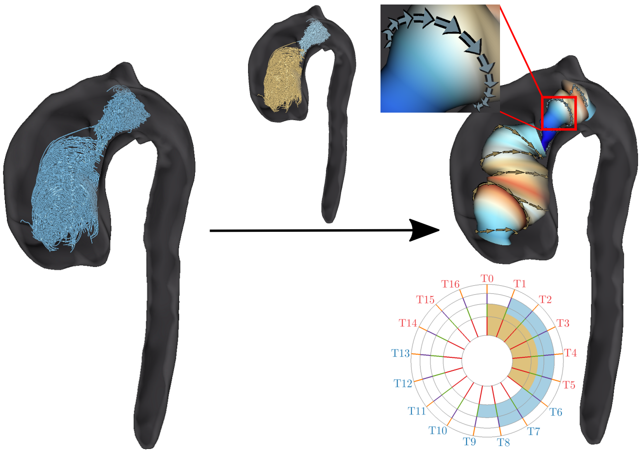

Figure 2: *Our semi-automatic vortex classification applied to a patient dataset with an aortic dilation. Starting from the path lines, two clusters are generated that are visualized by a 2D plot and a 3D glyph [MKP*16].*

Vortex Size. The manual determination of the vortex size has been described as very difficult. The experts have to view the vortices from many perspectives. AVOLCA's percentage size calculation enables a distinction of minor and pronounced vortices. In all cases, the calculated vortex size corresponded with the manual expert classification. However, in four cases AVOCLA under- or overestimated the size, respectively. In these cases, the assumed normal distribution of the path line points that is used for the size calculation is not satisfied. This can also cause that the glyph drops out of the vessel surface. In addition, the user study showed that the color-coded 3D glyph simplifies the size determination compared to the PV. Using the 3D glyph one wrong classification was given, whereas 7 assessments were not correct based on the PV. Similar to the experts, the subjects describe the size estimation based on the PV as difficult, because of the high interaction effort that is needed to see the vortex of all sides. Furthermore, they were unsure with the estimation of the distance between the vortex and the vessel wall.

Rotation Direction. The experts describe the classification of the RD as difficult for vortices that exhibit a difficult distribution of the RD or were located in the poorly visible descending aorta. AV-

OCLA calculated the RD, depending on which direction is more present in the vortex and could determined a correct result for 28 vortices. Two vortices run neither right- nor left-handed after manual assessment. Instead, the path lines run orthogonal to the centerline. We called this rotation *roll over rotation*, which cannot be detected by AVOCLA until now. Moreover, the arrow rendering was described as suitable to represent the RD. All subjects determined the correct RD using the 3D glyph. Using the PV, the subjects characterized the assessment as difficult, especially for vortices without a clear RD. This leads also to wrong classifications and a reduced certainty. The glyph abstracts the partially complex flow data and is therefore more appropriate to depict the RD, especially for more difficult cases. Using the PV, the detection of the correct RD is highly dependent on the complexity and location of the vortex.

Summary. In summary, AVOCLA's results correlate with the manual classifications in at least 86 % of the vortices, depending on the considered property. In addition, the manual classification was far more time-consuming and has been described as very exhausting by the experts. Processing the 15 datasets manually took 3h, whereas AVOCLA had a computation time per case between 12 and 20 s, depending on the amount of path lines. Moreover, for the manual classification the colored clustering of the vortices supports their visual perception and classification by the experts. In real clinical studies, no color-coding of clustered vortices is present that probably increases the difficulty and required time for a classification. In addition, the user study confirmed the suitability of our vortex visualizations to represent the classification results. The subjects described our techniques as simpler compared to the PV and they were able to determine the correct answer in almost all cases.

4. Discussion

We presented the development process of the method AVOCLA for a semi-automatic classification of aortic vortex flow extracted from 4D PC-MRI data. Our framework enables an objective and comparable vortex characterization, which is the basis for a deeper understanding of CVDs. We analyzed and discussed the previous manual vortex classification with our collaborating experts that was described as a time-consuming and not standardized process. Moreover, we identified five important vortex properties for the classification: shape, temporal occurrence, vessel section, size, and RD. Furthermore, we derived specific classification requirements from consultations with our domain experts. Based on this, we were able to design a computer-based classification of aortic vortices. The first step comprises the determination of vortex entities. Therefore we choose an agglomerative hierarchical approach [MLK*16] that is robust against noise and able to separate spatio-temporally adjacent vortices. For each clustered vortex, AVOCLA determine the five characteristics automatically. A common advantage of the clustering and classification is the possibility to incorporate expert knowledge. By manually editing, the expert is allowed to deal with various aortic shapes caused by different CVDs. Furthermore, our results are able to extend the binary expert classifications such as the vortex shape.

The calculated vortex properties are presented by a 2D and 3D visualization. The 2D depiction in form of a circular plot shows the spatio-temporal vortex behavior without any occlusions. The 3D representation approximates the vortex shape and displays the size as well as the RD by using a color-coding and arrow glyphs. The results of a qualitative expert evaluation and a performed user study confirmed the ability of AVOCLA to enable a reliable and objective vortex classification. Although we evaluated AVOCLA with positive feedback, some issues still need to be improved. In the future, the experts want to have a clear depiction of the vortex shape. Moreover, the calculation of the vortex size should be further enhanced. Possible under- or overestimations should be reduced by using optimization methods for the calculation of the enclosed surface. In addition, the wall motion should be considered, since the vortex size is changing relative to the expansion or contraction of the vessel wall. Furthermore, other experts should be included in the evaluation of AVOCLA's results and we have to check the extent to which a more detailed subdivision of the size or RD improves the binary classification from a medical point of view.

References

[BSK*14] Burris N. S., Sigovan M., Knauer H. A., Tseng E. E., Saloner D., Hope M. D.: Systolic flow displacement correlates with future ascending aortic growth in patients with bicuspid aortic valves undergoing magnetic resonance surveillance. *Investigative radiology 49*, 10 (2014), 635–639. 1

[DBB*15] Dyverfeldt P., Bissell M., Barker A. J., Bolger A. F., et al.: 4D Flow Cardiovascular Magnetic Resonance Consensus Statement. *J Cardiovasc Magn Reson 17*, 1 (2015), 72. 1

[GBvO*15] Guzzardi D. G., Barker A. J., van Ooij P., Malaisrie S. C., Puthumana J. J., Belke D. D., Mewhort H. E., Svystonyuk D. A., Kang S., Verma S., et al.: Valve-related hemodynamics mediate human bicuspid aortopathy: insights from wall shear stress mapping. *Journal of the American College of Cardiology 66*, 8 (2015), 892–900. 1

[GMH*12] Geiger J., Markl M., Herzer L., Hirtler D., Loeffelbein F., Stiller B., Langer M., Arnold R.: Aortic Flow Patterns in Patients with Marfan Syndrome assessed by Flow-Sensitive Four-Dimensional MRI. *J Magn Reson Imaging 35*, 3 (2012), 594–600. 1

[HHM*10] Hope M. D., Hope T. A., Meadows A. K., Ordovas K. G., Urbania T. H., Alley M. T., Higgins C. B.: Bicuspid Aortic Valve: Four-Dimensional MR Evaluation of Ascending Aortic Systolic Flow Patterns. *Radiology 255*, 1 (2010), 53–61. 1

[HMW*07] Hope T. A., Markl M., Wigström L., Alley M. T., Miller D., Herfkens R.: Comparison of Flow Patterns in Ascending Aortic Aneurysms and Volunteers using Four-Dimensional Magnetic Resonance Velocity Mapping. *J Magn Reson Imaging 26*, 6 (2007), 1471–9. 1

[HWS*12] Hope M. D., Wrenn J., Sigovan M., Foster E., Tseng E. E., Saloner D.: Imaging Biomarkers of Aortic Disease - Increased Growth Rates with Eccentric Systolic Flow. *J Amer Coll Cardiol 60* (2012), 356–7. 1

[KGP*13] Köhler B., Gasteiger R., Preim U., Theisel H., Gutberlet M., Preim B.: Semi-Automatic Vortex Extraction in 4D PC-MRI Cardiac Blood Flow Data using Line Predicates. *IEEE Trans Vis Comput Graph 19(12)* (2013), 2773–82. 2

[KYM*93] Kilner P., Yang G., Mohiaddin R., Firmin D. N., Longmore D. B.: Helical and Retrograde Secondary Flow Patterns in the Aortic Arch Studied by Three Directional Magnetic Resonance Velocity Mapping. *Circulation 88* (1993), 2235–47. 1

[MBS*15] Mahadevia R., Barker A. J., Schnell S., Entezari

P., KANSAL P., FEDAK P. W. M., MALAISRIE S. C., MCCARTHY P., COLLINS J., CARR J., MARKL M.: Bicuspid Aortic Cusp Fusion Morphology Alters Aortic 3D Outflow Patterns, Wall Shear Stress and Expression of Aortopathy. *Circulation 129*, 6 (2015), 673–82. 1

[MKP*16] MEUSCHKE M., KÖHLER B., PREIM U., PREIM B., LAWONN K.: Semi-automatic Vortex Flow Classification in 4D PC-MRI Data of the Aorta. *Computer Graphics Forum (Eurographics Conference on Visualization (EuroVis) 2016)* (2016), to appear. 1, 2, 3

[MLK*16] MEUSCHKE M., LAWONN K., KÖHLER B., PREIM U., PREIM B.: Clustering of Aortic Vortex Flow in Cardiac 4D PC-MRI Data. In *Proc: Bildverarbeitung für die Medizin* (2016), pp. 182–187. 1, 2, 3, 4

[MPN11] MENDIS S., PUSKA P., NORRVING B.: Global atlas on cardiovascular disease prevention and control. *World Health Organization, World Heart Federation and World Stroke Organization* (2011). 1

[vOPP*16] VAN OOIJ P., POWELL A. L., POTTERS W. V., CARR J. C., MARKL M., ET AL.: Reproducibility and interobserver variability of systolic blood flow velocity and 3d wall shear stress derived from 4d flow mri in the healthy aorta. *Journal of Magnetic Resonance Imaging 43*, 1 (2016), 236–248. 1