Hierarchical Shape Distributions for Automatic Identification of 3D Diastolic Vortex Rings from 4D Flow MRI

Mohammed S.M. Elbaz[1], Boudewijn P.F. Lelieveldt[1,2], and Rob J. van der Geest[1]

[1] Division of Image Processing, Department of Radiology,
Leiden University Medical Center, Leiden, The Netherlands
[2] Department of Intelligent Systems, Delft University of Technology, Delft, The Netherlands
mohammed.elbaz@lumc.nl

Abstract. Vortex ring formation within the cardiac left ventricular (LV) blood flow has recently gained much interest as an efficient blood transportation mechanism and a potential early predictor of the chamber remodeling. In this work we propose a new method for automatic identification of vortex rings in the LV by means of 4D Flow MRI. The proposed method consists of three elements: 1) the 4D Flow MRI flow field is transformed into a 3D vortical scalar field using a well-established fluid dynamics-based vortex detection technique. 2) a shape signature of the cardiac vortex ring isosurface is derived from the probability distribution function of pairwise distances of randomly sampled points over the isosurface 3) a hierarchical clustering is then proposed to simultaneously identify the best isovalue that defines a vortex ring as well as the isosurface that corresponds to a vortex ring in the given vortical scalar field. The proposed method was evaluated in a datasets of 24 healthy controls as well as a dataset of 23 congenital heart disease patients. Results show great promise not only for vortex ring identification but also for allowing an objective quantification of vortex ring formation in the LV.

1 Introduction

A growing body of evidence [1-6] suggests a critical role of vortex ring formation within cardiac left ventricular blood flow during diastole as a significant contributor to efficient blood transportation [2] and as a potential clinical biomarker for early prediction of cardiac remodeling and diastolic dysfunction [4,5]. A vortex is generally characterized by a swirling motion of a group of fluid elements around a common axis. Among different types of vortical flow structures, vortex rings are most abundant in nature due their stability [6]. In the LV, the asymmetrical redirection of blood flow through the LV results in the development of a vortex ring distal to the mitral valve (Fig.1) [1].

In fluid dynamics, different methods exist to define a vortex structure [7]. Most of these methods are based on a function of the velocity gradient tensor of the flow field. 4D Flow MRI enables non-invasive acquisition of the blood flow velocity field

N. Navab et al. (Eds.): MICCAI 2015, Part II, LNCS 9350, pp. 467–475, 2015.
DOI: 10.1007/978-3-319-24571-3_56

providing all three velocity components (in-plane and through-plane) over the three spatial dimensions and over the cardiac cycle [1]. Therefore, 4D Flow MRI provides all the flow field information needed for 3D vortex analysis [3].

A typical 3D vortex ring identification problem consists of three steps 1) convert the 3D velocity flow field into some 3D vortical scalar field in which a vortex is defined given some criteria; 2) manually (empirically) select an isovalue threshold that can define a vortex ring structure from the 3D vortical field. Given that different vortex structures may be present in the same flow field, the selected isovalue may result in multiple co-existing isosurfaces of other vortex structures in addition to the target vortex ring. 3) Manually identify the isosurface that corresponds to a vortex ring. It is obvious that manual isovalue selection and vortex ring selection can be time consuming and subjective. This may limit the applicability of a 3D vortex ring analysis in a clinical setup in which objective and reproducible analysis is crucial.

To our knowledge, there have been no studies on fully automatic identification of a vortex ring (i.e. both steps 2 and 3) from 4D Flow MRI. In our previous work [8], only the automatic identification of a vortex ring (step 3) was addressed using a spectral shape analysis [9]. However, this was based on the assumption that an isovalue was already predefined; therefore the problem of automatic isovalue selection has not been addressed. In addition, spectral shape analysis can be computationally intensive, hence may not be suitable for a multi-level search.

In this work, we propose a new method that simultaneously and automatically identifies the isovalue and the vortex ring isosurface. The proposed method has three elements: First, the flow field from peak inflow phase of 4D Flow MRI is converted into a 3D vortical scalar field using a well-established fluid-dynamics-based vortex identification method called the Lambda2 method [10]. Second, a reference shape signature defining the vortex ring isosurface is computed from a training set using D2 shape distributions [11]. Finally, simultaneous identification of isovalue and vortex ring is achieved using hierarchical clustering that allows for an iterative search for the best D2 shape distribution match with the reference signature. To evaluate the objectivity and generalizability of the proposed method in a clinical setup, the defined vortex ring was quantified using the method introduced in [3] in a dataset of 24 healthy controls as well as in a challenging dataset of 23 congenital heart disease patients who were previously reported to have abnormal diastolic inflow [12].

2 Methodology

2.1 3D Vortical Scalar Field from 4D Flow MRI Using the Lambda2 Method

Among different fluid dynamics based vortex identification methods [7], the lambda2 (λ_2) method is considered the most accepted definition of a vortex [6]. The lambda2 method extracts vortex structures from the flow field by means of vortex-cores. The input for the Lambda2 method is the three velocity components of the velocity vector field and the output is a 3D scalar field in which each voxel is assigned a scalar value (λ_2). This scalar value can then be used to determine whether or not a voxel belongs to a vortex. For more formal definition, if U, V and F denote the three velocity components of the flow field acquired using 4D Flow and X, Y, Z denote the three spatial dimensions each of size $I \times J \times W$ with I as 4D Flow MRI's slice width, J as its height and W as the number of slices. Then the λ_2 method can be applied as follows. First, the velocity gradient tensor $\mathbf{J}$ is computed. Second, the tensor $\mathbf{J}$ is decomposed into its symmetric part, the strain deformation tensor $\mathbf{S} = \frac{\mathrm{J+J^T}}{2}$ and the antisymmetric part, the spin sor $\mathbf{\Omega} = \frac{\mathrm{J-J^T}}{2}$, where T is the transpose operation. Then, eigenvalue analysis is applied only on $\mathbf{S}^2 + \mathbf{\Omega}^2$**.** Finally**,** a voxel is labeled as part of a vortex only if it has two negative eigenvalues i.e. if $\lambda_1, \lambda_2, \lambda_3$ are the eigenvalues whereas $\lambda_1 \geq \lambda_2 \geq \lambda_3$ then a voxel is labeled as vortex if its $\lambda_2 < 0$. Isosurfaces of a λ_2 isovalue threshold (T_{λ_2}) <0 can be used to visualize different vortex structures in the flow field. A single T_{λ_2}isovalue can result in multi isosurfaces of different vortex structures among which a vortex ring may or may not be present. Different T_{λ_2}isovalues can be used to reveal different levels of details of vortices in the flow.

There are two outputs of this step. 1) A 3D volume denoted by $\boldsymbol{L_{i,j,w}}$ where

$$\boldsymbol{L_{i,j,w}} = \begin{cases} 0, & \mathit{if}\ \lambda_2(i,j,w) \geq 0 \\ \lambda_2(i,j,w) & \mathit{if}\ \lambda_2(i,j,w) < 0 \end{cases}, i = 1, \dots I. j = 1, \dots J.\ w = 1, \dots W.$$

2) A 1D feature vector Q_d , $d = 1, \dots P$ that stores all scalar values $\boldsymbol{L_{i,j,w}} \neq 0$ (i.e. all possible T_{λ_2}thresholds)**.** Q_d represents the isovalue feature vector. P represents the total number of scalar values $\boldsymbol{L_{i,j,w}} \neq \mathbf{0}$**.**

Throughout the rest of the paper, the term vortex refers to a vortex core under the λ_2 definition explained above.

3 D2 Signature of Shape Distributions

The signature of shape distributions was first introduced in [11] for shape retrieval in computer vision tasks. The idea behind shape distributions' signature is to statistically encode a 3D model using a probability distribution of some parametric function that measures geometric properties of the given 3D model. This reduces the shape matching/retrieval problem into a simple distribution comparison [11]. D2 signature (Fig.1) is a shape distribution signature where the parametric function is defined by the Euclidean distances between randomly sampled pairs of points over the 3D surface. The D2 distribution can globally define the surface of interest (in our case, the vortex ring isosurface). Compared to other global shape signatures e.g. spectral signatures [9], the major advantage of the D2 distribution signature is its simplicity, essentially the shape matching problem is reduced to random sampling of points, histogram construction and finally histogram comparison using a dissimilarity metric.

Being a distribution, the D2-signature is invariant to rotation, translation and scaling (after normalization), therefore allowing matching of different shapes without the need for pre-registration or alignment. In addition, it is robust to small shape perturbations or deformations (e.g. due to noise) [11] which makes it sufficient for tasks that require multi shape comparisons as in our case.

In this work, the D2 signature is constructed following a similar procedure to that proposed in [11]: 1) Represent the 3D shape of interest as an isosurface. 2) Randomly sample $\boldsymbol{N}$ point pairs over the vortex-ring isosurface. $\boldsymbol{N}$=512^2 pair of samples was used in this work. 3) Compute Euclidean distances between the $\boldsymbol{N}$ samples using L2-norm. 4) Construct a histogram of $\boldsymbol{B}$ bins of the pairwise distances. $\boldsymbol{B}$ =100 equally space bins was used in this work. 5) Normalize the resulting histogram using root mean square deviation. This step makes the signature scale invariant. 6) Define a dissimilarity metric to be used for histogram matching with a new given 3D model. In this work we used the normalized L1-norm (normalized by L1 norm of the reference signature) as dissimilarity metric. Though similar, cardiac vortex rings differ between subjects. To account for this, we derive an average reference signature from a cohort of healthy subjects for matching purposes. Of note, increasing $\boldsymbol{N}$ and $\boldsymbol{B}$ more than the specified numbers did not yield significant improvement.

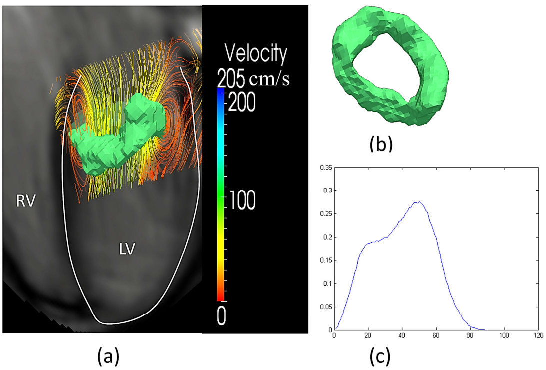

Fig. 1. (a) A four chamber view showing the 3D vortex ring isosurface (in green) with super-imposed streamlines in the LV at peak inflow phase in a sample healthy subject. (b) Separate view of the 3D vortex ring isosurface shown in (a). (c) The reference (average) D2 shape distributions' signature determined from the 24 healthy controls in this study.

4 Hierarchical Shape Distributions for Vortex Ring Identification

In principle, the vortex ring isosurface may be defined by any isovalue in the Q_d feature vector. This can result in a large search space as multiple shape matching tasks are needed per each value to find the target isosurface. To reduce the search space, we propose to compress the isovalue feature vector into a subset of representative isovalues using the vector quantization technique [13]. Given a vector of features, the vector quantization process involves compression of the input set of points into a smaller set. This works by dividing the input vector into groups, each group is then defined by one value given some criteria [13]. The well-known K-means clustering algorithm is a vector quantization method [13] in which a long input feature vector can be compressed into a vector of K cluster centroids that minimize the within-cluster sum of square distances.

In this work, we use an iterative hierarchical K-means scheme in which there is no need to predefine the number of centroids K. This allows avoiding the possible bias when K is predefined. The proposed scheme is as follows: Given the isovalue feature vector Q_d, initialize with K=1 and apply the K-means clustering algorithm (i.e. Q_d feature vector is reduced to a single candidate isovalue). Then, K is iteratively incremented by one until convergence or a predefined stopping criterion is satisfied. This results in a hierarchical multi-level vector $V^{r,k}$, in which each level $k = 1, \dots P$ carries $r = 1, \dots k$ candidate isovalues.

Given an isovalue level k, each isovalue $V^{r,k}$ can define $U_t^{r,k}, t = 1, \dots E$ isosurfaces of different vortex structures from among them a vortex ring may or may not be present. Therefore, to identify the vortex ring isosurface we need to solve two problems. 1) Find the isovalue $V^{r,k}$ in which a vortex ring is one of its E resulting isosurfaces. 2) Find the isosurface $U_t^{r,k}$ that corresponds to a vortex ring.

Using the proposed hierarchical vector quantization scheme and the reference D2 shape distribution signature, we are able to simultaneously solve these two problems by minimizing the shape distribution distances as follows: for each isovalue $V^{r,k}$ at level k, extract the corresponding $U_t^{r,k}$ vortex isosurfaces. Then, for each isosurface $U_t^{r,k}$, construct the D2 shape distribution following the procedure explained above. Compute the dissimilarity distance $d_t^{r,k}$ with the reference signature using the normalized L1 norm (i.e. normalized by the L1-norm of the reference signature). Repeat this for every isovalue level until convergence ($d_t^{r,k} < \epsilon$) or stopping criteria is satisfied. We wish to identify the best surface match by finding the indices $\hat{r}, \hat{k}$ *and* $\hat{t}$ such that

$$\{\hat{r}, \hat{k}, \hat{t}\} = arg\min_{r,k,t} d$$

As a result the target two problems are simultaneously solved by defining the isosurface $U_{\hat{t}}^{\hat{r},\hat{k}}$ as the target vortex ring isosurface and corresponding isovalue $V^{\hat{r},\hat{k}}$ as the target isovalue. To avoid local minima, for each iteration, the K-means algorithm was replicated T times (T =10 was used in this work) using different initial centroids. Then, the centroids with minimum within-cluster sums of point-to-centroid distances were chosen. Two stop criteria were defined 1) reaching a maximum number of predefined iterations (set to 50 in this work). In all our experiments, less than 15 iterations were enough to find $\{\hat{r}, \hat{k}, \hat{t}\}$, and 2) The dissimilarity distance was increasing for three consecutive iterations. This decreases the possibility of stopping at local minima when only a single diverging iteration is used instead.

5 Quantitative Characterization of the Identified Vortex Ring in the LV

After the identification of the vortex ring isosurface, it was quantified using the parameters proposed in [3]. These parameters are the vortex ring orientation and normalized cylindrical (Circumferential (C), Longitudinal (L) and Radial(R)) 3D position of the vortex ring center relative to the LV. L and R were normalized relative to the LV long-axis length and the radius of the LV endocardial cavity, respectively. Vortex orientation is defined as the angle between the LV long axis and the fitting plane of the vortex isosurface.

6 Dataset, Preprocessing and Validation

We evaluated the proposed method on two datasets: one dataset of 24 healthy controls (mean age: 21±10 years) as previously described in [3] and a dataset of 23 patients (27±11) after atrioventricular septal defect correction. All subjects underwent retrospectively-gated 4D Flow MRI at 3.0 T (Philips) with spatial resolution of 3-4 mm^3 and a temporal resolution of ~30 ms covering all 4 chambers of the heart. This data was then linearly interpolated spatially to result in a 1mm^3 spatial resolution. More details on the acquisition parameters can be found in [3].

To localize the LV ROI, the LV was manually segmented from only the peak-inflow diastolic phase in the 4D Flow volume as explained in [3]. As the vortex ring is a connected region of voxels within the LV, accurate segmentation is not required for the purpose of vortex ring identification. Only rough over-segmentation of the LV (to ensure the LV is covered) was enough to roughly define the LV ROI. In this work, an over-segmentation of about 0.5 cm around LV border was used to define LV ROI.

To generate the ground truth for the vortex ring isosurface in the two included datasets, for the healthy control dataset, we used the vortex ring isosurfaces interactively generated with low inter and intra observer variability in a previously validated workflow [3]. Same procedure in [3] was used to blindly generate the ground truth for patient dataset. To quantitatively evaluate the performance of the proposed method in the first dataset of healthy controls, leave-one-out cross-validation was used to avoid bias in the selection of the reference averaged D2 signature.

To test the generalization performance in a clinical setting, the dataset of 23 patients was evaluated using a reference signature derived only from the 24 healthy control subjects. To evaluate the identification performance relative to the ground truth, we performed two sets of evaluations. The accuracy of the identified isosurface object was assessed using the Hausdorff distance and dice coefficient for surface overlap. In addition, a paired student's t-test comparison of the automatically defined isovalues and the one used to generate the ground truth isosurfaces was performed. Second, paired student's t-test was used to statistically compare the quantitative vortex ring parameters of the automatically identified vortex-ring isosurfaces to those of the ground truth. For all statistical tests a p-value <0.05 was considered significant.

7 Results

In all subjects of both datasets, a vortex ring isosurface was successfully identified from the Lambda2 scalar field with qualitatively similar shape to that of the ground truth (Fig. 2). Detailed results of the quantitative evaluation over the two datasets is given in Table 1 where a Hausdorff distance of 8.36±7.55 mm in healthy control dataset and 11.73±6.57 mm in the patients dataset were found. The surface overlap (dice coefficient) was 0.81±0.09 in controls and 0.77±0.14 in patients. The identified isovalues using the proposed method were highly comparable to those of the ground truth and not statistically different (p=0.86). Quantitative parameters of the automatically identified vortex rings were in good agreement with the ground truth.

8 Discussion and Conclusion

This paper presents a framework for objective identification and quantification of 3D vortex ring in the LV from 4D PC MRI by means of isosurfaces. The problem of vortex ring identification from the 3D vortical scalar field was reduced to histogram comparison and hierarchical K-means vector quantization. The reported results on healthy controls as well as patients show great promise of the proposed method. The generalizability of the proposed method was evaluated with abnormal vortex rings being identified from 23 patients with a signature trained solely on normal vortex ring isosurfaces from healthy controls. The proposed method provided high performance and agreement with the blindly generated ground truth. It is important to emphasize that the exact size/volume of a vortex ring is generally undefined as it is isovalue dependent. Therefore, volumetric measurements like Hausdorff distance or dice overlap may not sufficiently capture the validity of the identified vortex rings. Instead, the evaluated quantitative characterization parameters (C, L, R and orientation) may provide more objective evaluation of the method and its potential clinical value. In this work, the vortex ring identification was limited to the phase of peak LV inflow which is considered the moment around full vortex development [3,6], however vortex formation in the LV is a dynamic process over the entire diastole involving vortex evolution and dissipation with corresponding shape deformations. Future work will address the method's performance in other diastolic phases. The proposed method allows for objective quantitative characterization of the peak-inflow vortex ring formation in the LV with results comparable to those previously validated [3]. With the increasing interest in vortex ring formation as a potential biomarker for LV (dys)function [2,4,6], the proposed method can play an important role in providing objective 3D vortex analysis for assessment of vortex ring formation in the LV from 4D Flow MRI.

Table 1. Qunatitative evaluation results

Parameter	24 Controls			23 Patients		
	Ground truth	Proposed method	p-value (paired t-test)	Ground truth	Proposed method	p-value (paired t-test)
C	87±20	85±24	0.12	67±19	63±23	0.07
L	0.19±0.04	0.19±0.04	0.92	0.22±0.06	0.22±0.05	0.74
R	0.27±0.07	0.27±0.07	0.91	0.33±0.09	0.33±0.1	0.61
Vortex Orientation	70±55	65±54	0.65	57±25	57±40	0.87
Lambda2 Isovalue*	-7.2±-3.43	-7.3±-3.2	0.82	-7.27±-11.24	-7.7±-5.45	0.86
Surface Overlap (Dice Coeffecient)	0.81±0.09			0.77±0.14		
Hausdorff distance (mm)	8.36±7.55			11.73±6.57		

*The absolute lambda2 isovalue doesn't have direct interpretation here and was provided only to give impression on how similar were they in test cases compared to ground truth

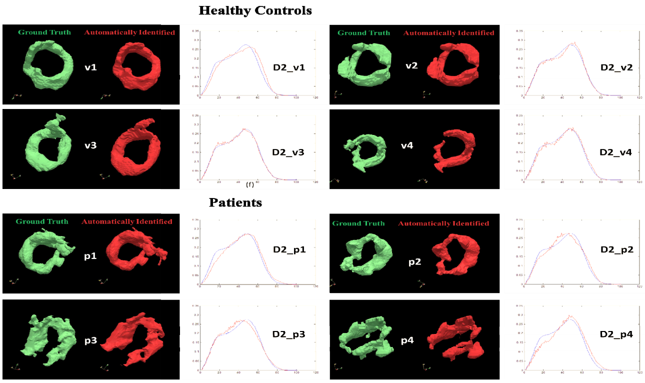

Fig. 1. Sample results of the proposed method on 4 healthy controls (top two rows: v1 to v4) and 4 patients (bottom two rows: p1 to p4). For every subject, the ground truth is presented on left (green) and the automatically identified peak-inflow vortex ring isosurface on right (red). D2_v1 to D2_v4 and D2_p1 to D2_p4 show the best matched D2 distributions corresponded to the automatically identified vortex ring isosurface (red curve) overlaid on the reference signature (average over healthy controls) in blue.

Acknowledgement. This work is supported by Dutch Technology Foundation (STW): project number 11626.

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