# MODEL-BASED FLOW QUANTIFICATION USING CONDITIONAL RANDOM FIELDS WITH GLOBAL PREFERENCES

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## ABSTRACT

Recent advances in the real-time 3D full volume echocardiography have enabled high frame rate acquisition of volumetric color Doppler flow images. In this paper, we propose a fully automated method for de-aliasing of color Doppler flow and quantification of the cardiac flow using instantaneous 3D+t ultrasound data. First, the anatomical information, such as mitral annulus and left ventricle outflow tract (LVOT), are detected and tracked automatically accounting for the heart motion. 3D planes are constructed at the estimated mitral annulus and LVOT locations to sample the color flow data. To overcome inherent limitation of the color Doppler velocity ambiguity caused by the Nyquist velocity level, we formulate the de-aliasing process in a conditional random field (CRF) framework and introduce a global consistency potential to incorporate domain specific prior information based on the instantaneous change in LV volume. Preliminary results with clinical data presented here agree well with clinical measurements in a quantitative manner. The proposed method is efficient and achieves high speed performance of $0.2$ second per volume of ultrasound data.

***Index Terms***— Color Doppler, Cardiac Flow Quantification, Conditional Random Fields, Learning-based Methods

## 1. INTRODUCTION

Valvular heart diseases are recognized as a significant cause of morbidity and mortality. The quantification of cardiac flow volumes in patients is essential in evaluation of the progression of the disease and in determination of clinical options. However, accurate flow measurement remains a significant challenge for cardiologists [1]. Doppler ultrasound is a non-invasive and cost effective method for evaluation of intracardiac blood flow and for assessment of cardiac function. With real-time full volume echocardiography it is now feasible to acquire transthoracic 3D color flow imaging (CFI) for every heartbeat (without stitching) such that both mitral valve and LVOT can be covered by color Doppler region of interest. However, flow velocity aliasing [2] remains a fundamental limitation which can introduce significant errors in flow quantification directly using color Doppler data. The velocity ambiguity cannot be overcome just by ultrasound data especially when true velocity is several multiples of the Nyquist level [3]. To address this issue, various approaches have been proposed using customized hardware [4], and certain geometric or smoothness assumptions [5, 6, 7, 8, 9].

In this paper, we propose a fully automated method for color Doppler velocity de-aliasing and cardiac flow volume quantification using instantaneous 3D+t ultrasound data. More specifically, our method automatically detects both the mitral annulus and left ventricular outflow tract (LVOT) and places measurement planes at appropriate locations. To compensate non-rigid heart motion, measurement planes are tracked through the whole cardiac cycle to adjust the sampling locations and orientations in each frame. Furthermore, to recover the de-aliasing factor of the color Doppler flow data, we formulate the de-aliasing process in a conditional random field (CRF) framework [10, 11] and introduce a global consistency potential [12] to incorporate a domain specific prior information based on the instantaneous change in LV volume. To demonstrate the performance, we evaluated our method on a clinical dataset taken from 20 normal subjects, with a quantitative comparison to magnetic resonance imaging (MRI) flow measurements. The strong agreement to the MRI measurements demonstrates the good performance of our proposed method.

## 2. FRAMEWORK

In this section, we present the new framework to estimate 3D volume of both the mitral inflow and LVOT outflow, which includes the following main steps:

1. Automatic anatomy detection and tracking: The 3D location of the left ventricle, including the ventricular wall, the mitral annulus, and the left ventricular outflow tract (LVOT), is automatically detected in the first frame and tracked in the subsequent frames using a Bayesian approach [14] followed by mean-shift [15] based local refinement.

- Automatic detection of LV, mitral annulus, and LVOT locations $X_0$ on the first frame using the marginal space learning (MSL) approach [13]. Construct the sampling planes $\mathcal{V}$ at the mitral annulus and LVOT on the first frame.
- For each frame $t = 1, \ldots, T-1$ ($T$ is total frame number)
  **Input:** LV and sampling plane locations $X_{t-1}$ from the previous frame $t-1$
  **Output:** Estimated de-aliasing factor $f_i^{(t)}, i \in \mathcal{V}$ for each sampling point and flow volume $Vf_t$

  1. Track LV and sampling plane locations $X_t$ in frame t,

     $$\arg\max_{\vec{X}_t} p(\vec{X}_t|\vec{Y}_{0:t}) = \arg\max_{\vec{X}_t} p(\vec{Y}_t|\vec{X}_t)p(\vec{X}_t|\vec{Y}_{0:t-1})$$

     where $\vec{Y}_{0:t} = (\vec{Y}_0, \ldots, \vec{Y}_t)$ and $\vec{X}_t = [\vec{x}_1, \cdots, \vec{x}_n]$ are the local features and the mesh point positions, respectively, defined in Sec. 2.1. This is solved by the optimization technique in [14] followed by a mean shift algorithm [15] for local refinement.
  2. for each sampling plane, estimate the de-aliasing factor $f_i^{(t)}, i \in \mathcal{V}$ for each sampling point by optimizing the following energy function defined in Sec. 2.2,

     $$\sum_{i\in\mathcal{V}} \phi(f_i^{(t)}) + \sum_{(i,j)\in\varepsilon_L} \psi_L(f_i^{(t)}, f_j^{(t)}) + \sum_{(i,g)\in\varepsilon_G} \psi_L(f_i^{(t)}, f_g^{(t)})$$

     where $\phi(f_i^{(t)})$, $\psi_L(f_i^{(t)}, f_j^{(t)})$, and $\psi_L(f_i^{(t)}, f_g^{(t)})$ are the data, smoothness, and global preference terms respectively, as defined in Sec. 2.2.
  3. Compute the flow volume as $Vf_t = \sum_{i\in\mathcal{V}} \hat{v}_i^{(t)} * dA_i^{(t)}$, where $\hat{v}_i^{(t)} = v_i^{(t)} + v_s f_i^{(t)}$ is the estimated velocity after de-aliasing and $dA_i^{(t)}$ is the unit area of each sampling point as illustrated in Fig. 1(c).

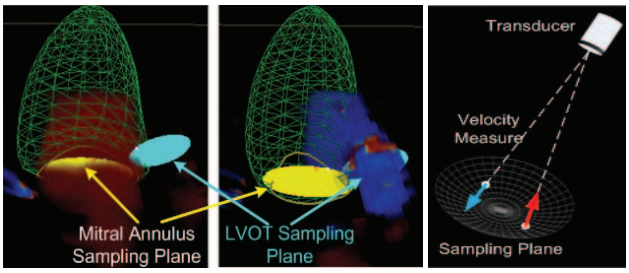
**Algorithm 1:** The outline of our automatic flow de-aliasing and quantification algorithm.

2. Flow de-aliasing and quantification: To recover the underlying velocity values from the aliased measurements, a conditional random field (CRF) model is built based on the flow sampling planes. Furthermore, a global constraint from the LV volume change between neighboring frames is introduced to remove the ambiguity of the de-aliasing factor estimation and consequently to increase the robustness of cardiac flow volume quantification using color Doppler images.

For clarity, the outline of our new algorithm is listed in Algorithm 1.

### 2.1. Learning-based 3D model detection and tracking

In the starting frame (typically the end-diastole cardiac phase), we detect automatically the endocardial boundary of the left ventricle (LV), the mitral annulus, and the left ventricular outflow tract (LVOT). A 3D detector is learned to locate the pose, including the position $X = (x, y, z)$, orientation $\theta = (\alpha, \beta, \gamma)$ and scale $S = (s_x, s_y, s_z)$, of the LV using the marginal space learning (MSL) approach [13]. The local deformations of the mitral annulus, the LVOT, and the ventricular wall boundary are further estimated based on the posterior distribution $p_i(X|I)$ of each control point on the surface, which is learned using the steerable features and the probability boosting-tree (PBT) [16].




(a) (b) (c)

**Fig. 1**. The anatomical model used to represent the left ventricle, mitral annulus, and left ventricular outflow tract (LVOT). (a) and (b) show the 3D model with sampling planes superimposed on the mitral inflow and LVOT outflow, respectively. (c) illustrates the measurement plane on a sphere centering at the tip of the ultrasound pyramid.

To represent the anatomical structure of the left ventricle, the mitral annulus, and the left ventricular outflow tract, a 3D mesh model is used in our system as illustrated in Fig. 1(a,b), where the mitral annulus and LVOT sampling planes are highlighted in the yellow and blue color, respectively. Because of the physical form of the 3D ultrasound pyramid, a plane in the acoustic space with a constant distance to the transducer corresponds to a sphere in the Cartesian space, centering at the tip of the pyramid as illustrated in Fig. 1(c). Therefore, the sampling planes in our model are defined on a sphere passing through the mitral annulus or the LVOT. To compute the volume of the mitral inflow and the LVOT outflow, we consider the area enclosed by the mitral annulus and the LVOT ring, as shown in Fig. 1(a,b).

Instead of detecting the above anatomical structure independently in each frame, a model-based tracking approach [14] is used to ensure temporal consistency and smooth motion and to avoid drifting and outliers, by optimizing the following Bayesian function

$$\arg\max_{\vec{X}_t} p(\vec{X}_t|\vec{Y}_{0:t}) = \arg\max_{\vec{X}_t} p(\vec{Y}_t|\vec{X}_t)p(\vec{X}_t|\vec{Y}_{0:t-1}) \quad (1)$$

where $\vec{Y}_{0:t} = (\vec{Y}_0, \ldots, \vec{Y}_t)$ are the measurements (including local features and image templates) from the first $t$ frames $I_{0:t} = (I_1, \ldots, I_t)$. For clarity, we use $\vec{X}_t$ to denote a concatenation of the mesh point positions, $\vec{X}_t = [\vec{x}_1, \cdots, \vec{x}_n]$, which need to be estimated at the current time instance $t$, and $n$ is the total number of points in the model.

Starting from the detection result at the initial frame, the model deformations are propagated to neighboring frames using both the learned features and the local image templates. Furthermore, based on the tracked mitral annulus and LVOT locations obtained from Eqn. 1, a local refinement step is

added to place the measurement planes accurately using the mean shift approach [15]. As a result, the flow volumes are computed consistently based on the anatomical structure of the left ventricle.

### 2.2. Flow de-aliasing using CRFs with global preferences

In color flow images, aliasing is a common issue which describes single or multiple exceeding of the color Doppler Nyquist velocity, causing ambiguity for velocities beyond the Nyquist level [3]. In this paper, we formulate the de-aliasing process in a conditional random field framework and introduce a global consistency potential to incorporate domain specific prior information based on LV volume changes.

Given the color flow data $v_i^{(t)}(i \in \mathcal{V})$ sampled on the measurement planes in Sec. 2.1, the goal is to recover the de-aliasing factor $f_i^{(t)}$ for each sampling point. Since $f_i^{(t)}$ is a non-negative integer (typically between $0 \sim 2$) representing the number of aliasing transitions, this can be naturally formulated as a conditional random field (CRF) model $\mathcal{G} = (\mathcal{V}, \varepsilon)$, where the set $\mathcal{V}$ is used for indexing random variables associated with each sampling point $v_i^{(t)}$, and $\varepsilon$ is the set of undirected edges representing compatibility relationships between random variables. The de-aliasing factor $f_i^{(t)}$ is the corresponding label for each node or random variable. Thus the energy function of graph $\mathcal{G}$ can be written as the sum of the unary and smoothness potentials, respectively:

$$\sum_{i \in \mathcal{V}} \phi(f_i^{(t)}) + \sum_{(i,j) \in \varepsilon_L} \psi_L(f_i^{(t)}, f_j^{(t)}) \tag{2}$$

where $\phi(f_i^{(t)})$ is the unary data term and $\psi_L(f_i^{(t)}, f_j^{(t)})$ is the smoothness potential. $\mathcal{V}$ are the indices associated with each sampling point and the set of local edges $\varepsilon_L$ is the pairwise connection between the local nodes.

However, there is an inherent ambiguity in the Eqn. 2 as each label $f_i$ can choose an arbitrary number without a global constraint, which might lead to an invalid flow volume. Fortunately domain-specific knowledge can be leveraged to remove this ambiguity, as the LV volume change and the flow volume measure the same amount of blood flow through the left ventricle at certain time instance. Given the tracked LV endocardial boundaries in the previous frame $t-1$ and the current frame $t$, we can compute the corresponding LV cavity volume as $V_{t-1}$ and $V_t$ respectively, and therefore the LV volume change as $dV_t = V_t - V_{t-1}$. Thus, the average number of aliasing transitions can be computed as

$$f_g = \lfloor \frac{dV_t \cdot fr}{\sum_i dA_i \cdot v_s} \rfloor \tag{3}$$

where $fr$ is the frame rate, $dA_i^{(t)}$ is the area of each sampling point, $v_s$ is the color Doppler Nyquist velocity. Please note that $f_g$ is a discrete value as the floor function $\lfloor \cdot \rfloor$ returns the largest non-negative integer not exceeding the value on the right-hand side. Consequently, Eqn. 2 can be augmented to incorporate the global reference $f_g$ as follows,

$$\sum_{i \in \mathcal{V}} \phi(f_i) + \sum_{(i,j) \in \varepsilon_L} \psi_L(f_i, f_j) + \sum_{(i,g) \in \varepsilon_G} \psi_G(f_i, f_g) \tag{4}$$

where $\psi_G(f_i, f_g)$ is the global consistency potential and the set of global edges $\varepsilon_G$ connects the global latent node with each of the local nodes. To simplify the notation we drop the frame index $^{(t)}$ in Eqn. 4 and the reminder of this section.

**Data Term:** The data term $\phi(f_i)$ encodes agreement between a label $f_i$ and the color flow data $v_i$. In this paper, we model it as a Gaussian distribution

$$\phi(f_i) = \frac{1}{\sqrt{2\pi\sigma_i^2}} e^{-\frac{(v_i + v_s f_i - \mu_i)^2}{2\sigma_i^2}} \tag{5}$$

where $v_s$ is the color Doppler Nyquist velocity. The two parameters, $\mu_i$ and $\sigma_i$ are learned from a training set. Fig. 2 shows an example of the mean flow velocity profile of mitral inflow and LVOT outflow.

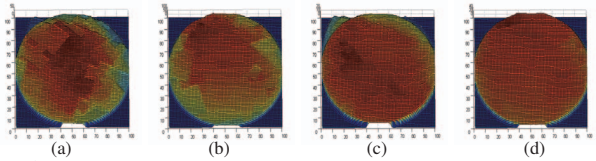



**Fig. 2**. An example of the average velocity profile for the mitral inflow (a) and the LVOT outflow (b) from 10 subjects. (c) and (d) are the computed standard deviation of the velocity values on the mitral inflow and the LVOT outflow, respectively. The dark red color shows high values while the light blue shows low values.

**Spatial Term:** The pair-wise term $\psi_L(f_i, f_j)$ encourages the spatial smoothness between neighboring nodes $f_i$ and $f_j$. For simplicity, we model it as a zero mean Gaussian distribution as

$$\psi_L(f_i, f_j) = \frac{\lambda_L}{\sqrt{2\pi\sigma_{ij}^2}} e^{-\frac{(f_i - f_j)^2}{2\sigma_{ij}^2}} \tag{6}$$

where $\lambda_L$ is the weighting factor for the spatial term in [12].

**Global Term:** The global potential $\psi_G(f_i, f_g)$ enforces the global consistency for each node. As shown in Eqn. 3, the global preference $f_g$ is computed based on the LV cavity volume change which can be incorporated as follows,

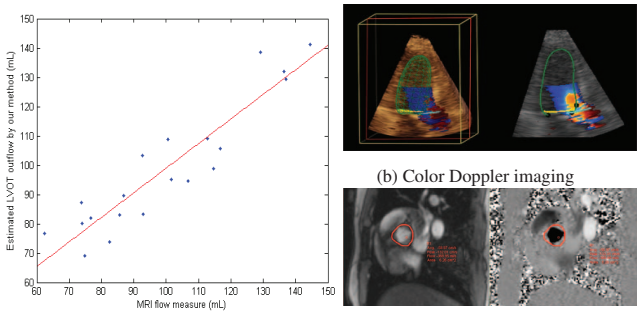
$$\psi_G(f_i, f_g) = \frac{\lambda_G}{\sqrt{2\pi\sigma_i^2}} e^{-\frac{(f_i - f_g)^2}{2\sigma_i^2}} \tag{7}$$

where $\lambda_G$ is the weighting factor for the global term. The weighting factors $\lambda_L$ and $\lambda_G$ for the spatial and global terms can be learned from the training dataset by iterating a two-step procedure until convergence as in [12].

## 3. EXPERIMENTAL RESULTS

To evaluate the performance of our method, a set of 3D+t volume ultrasound sequences were acquired by a Siemens

SC2000 scanner with an average volume rate of 22 vps. 20 subjects with normal valves were enrolled with the IRB approval and were not included in our training set. Fig. 3 reports the comparison between the flow volumes estimated by our method and the phase-contrast (PC) flow measurements using magnetic resonance imaging (MRI). The correlation between estimated flow volumes and the MRI measurements has a high score of 0.93, which demonstrates the accuracy and robustness of our method.




(a) Comparison to MRI measurement



(b) Color Doppler imaging



(c) MRI magnitude and phase images

**Fig. 3**. Flow measure comparison on 20 normal patients. (a) The horizontal axis shows the aortic flow volume measured by magnetic resonance imaging (MRI). The vertical axis is the de-aliased LVOT outflow based on the sampled color Doppler data by our method. The estimated flow volumes are consistent with the MRI measurements with a **high correlation score of** 0.93 (with an average difference of 1.0 ml), which demonstrates the accuracy and robustness of our proposed method. (b) shows an example of the 3D and 2D views of the volume color Doppler data. (c) shows an example of the magnitude (left) and phase (right) of MRI LV short axis acquisitions.

## 4. CONCLUSION

In this paper, we present a fully automatic method for flow de-aliasing and quantification on 3D real-time full volume ultrasound data. A 3D model is fitted automatically, using learned position and boundary detectors, to the left ventricle (LV), the mitral annulus, and the LVOT to construct measurement planes in a volumetric color Doppler image. To compensate heart motion, especially on the measurement planes, a model-based tracking approach is employed to propagate the inter-frame deformation through the whole cardiac cycle and to adjust the sampling locations and orientations in each frame. Given the tracked 3D model, a new approach is proposed to correct for aliasing in the color Doppler data using conditional random fields (CRFs). Furthermore, a global constraint is introduced in the CRF framework based on the LV volume change between two neighboring frames. Preliminary results on clinical data showed good correlation with MRI flow measurements. The proposed method is efficient and achieves high speed performance of 0.2 second per frame for volumetric ultrasound data.

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