OPTIMIZATION OF DOPPLER ECHOCARDIOGRAPHIC VELOCITY MEASUREMENTS USING AN AUTOMATIC CONTOUR DETECTION METHOD

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Abstract—Intra- and interobserver variability in Doppler echocardiographic velocity measurements (DEVM) is a significant issue. Indeed, imprecisions of DEVM can lead to diagnostic errors, particularly in the quantification of the severity of heart valve dysfunctions. To reduce the variability and rapidity of DEVM, we have developed an automatic method of Doppler velocity wave contour detection, based on active contour models. To validate our new method, results obtained with this method were compared with those obtained manually by two experienced echocardiographers on Doppler echocardiographic images of left ventricular outflow tract and transvalvular flow velocity signals recorded in 30 patients with aortic or mitral stenosis, 20 with normal sinus rhythm and 10 with atrial fibrillation. We focused on the three essential variables that are measured routinely using Doppler echocardiography in the clinical setting: the maximum velocity (Vmax), the mean velocity (Vmean) and the velocity-time integral (VTI). Comparison between the two methods has shown a very good agreement. A small bias value was found between the two methods (between –3.9% and 0.5% for Vmax, between –4.6% and –1.4% for Vmean and between –3.6% and 4.4% for VTI). Moreover, the computation time was short, ∼5 s. This new method applied to DEVM could, therefore, provide a useful tool to eliminate the intra- and interobserver variabilities associated with DEVM and thereby to improve the accuracy of the diagnosis of cardiovascular disease. This automatic method could also allow the echocardiographer to realize these measurements within a much shorter period of time compared with the standard manual tracing method. From a practical point of view, the model developed can be easily implemented in a standard echocardiographic system. (E-mail: emmanuel.gaillard@ircm.qc.ca)

Key Words: Doppler echocardiographic velocity measurements, Intra- and interobserver variability, Active contour model, Snake, Divergence centers.

INTRODUCTION

Doppler echocardiographic velocity measurements (DEVM) remain highly dependent on the person who performs them (Bjornstad et al. 1996; Galderisi et al. 1992; Grothues et al. 2002; Kupfahl et al. 2004). From DEVM data found in the literature, Margulescu et al. (2006) showed an important intra- and interobserver variability of DEVM. In addition, Kupfahl et al. (2004) have shown that the assessment variability of aortic stenosis severities by Doppler echocardiography was very high with both transthoracic and transoesophageal approaches (28% to 41% and 25% to 43%, respectively). The imprecision of DEVM can induce significant errors in the assessment of the severity of heart valve disease that might lead to nonoptimal management of patients. Accurate assessment of disease severity is crucial for selection of the appropriate treatment. It is therefore important to reduce intra- and interobserver variability when performing Doppler echocardiographic measurements. Moreover, the Doppler echocardiographic measurements are generally performed by manual tracing (using a track ball) on at least three cardiac cycles in patients with normal sinus rhythm and on five cardiac cycles in patients with atrial fibrillation. These measurements are thus time-consuming. In view of these observations, we developed an automatic method of Doppler velocity contour detection based...
on active contour models. Active contour models (or snakes) were first introduced by Kass et al. in 1988, and have quickly gained popularity in different domains. They have proven to be useful in medical image analysis (McInerney and Terzopoulos 1996; Sheshadri and Kandaswamy 2005; Singh et al. 1998) and for tracking moving objects in videos (Blake and Isard 1998; Liu et al. 2006; Terzopoulos and Szlinski 1992). The concept of snakes is based on curve detection through an optimization process. This optimization makes use of models of curve contrast and smoothness that use elastodynamic models and descriptions of their behavior under the application of external and internal forces.

Most of the methods used to automatically detect Doppler velocity contours are based on some form of noise reduction and edge-following algorithm (Cloutier et al. 1990; Doherty et al. 2002; Greenspan et al. 2005; Mo et al. 1988; Rickey and Fenster 1996; Tschirren et al. 2001). These methods consisted in performing first a time-frequency prefiltering, then a noise-thresholding and finally an edge detection. Another approach was proposed by Zhou et al. (2007) based on a probabilistic, hierarchical and discriminant framework for detection of deformable anatomic structures from medical images. The basic detection principle was to train a discriminant binary classifier to separate the deformable patterns of interest from the remaining part of the Doppler echocardiograms. They applied this framework to detect various deformable structures from Doppler echocardiograms. However, most of these methods are time consuming (Doherty et al. 2002; Greenspan et al. 2005) or lack accuracy (Zhou et al. 2007).

The objectives of this study were to develop a fast automatic method of Doppler velocity contour detection that could be implemented in standard echocardiographic systems, to reduce intra- and interobserver variabilities. For validation, data obtained with the new automatic detection method were compared with those obtained by the standard manual Doppler echocardiographic method.

METHODS

The active contour model (or snake) is an energy-minimizing spline whose energy depends on the snake’s form and position in the image (Kass et al. 1988). A snake is found after minimization of the energy functional, which is a sum of internal and external forces with weighting coefficients. A snake can be modeled as a parametric curve \( v(s, t) = (x(s, t), y(s, t)) \), where \( x \) and \( y \) are the coordinates of contour points, \( t \) is the current time or evolution step and \( s \in [0, 1] \) is the parametric domain and is proportional to the curve length. The energy functional that has to be minimized is defined as:

\[
E_{\text{snake}} = \int_0^1 E_{\text{in}}[v(s, t)]\,ds + \int_0^1 E_{\text{ex}}[v(s, t)]\,ds \quad (1)
\]

In this equation,

- The internal snake’s energy \( E_{\text{in}} \) characterizes the deformation of a stretchy, flexible contour, and can be decomposed into a first- and a second-order term.

\[
E_{\text{in}}[v(s, t)] = \frac{\alpha}{2} |v_s(s, t)|^2 + \frac{\beta}{2} |v_{ss}(s, t)|^2 \quad (2)
\]

where \( v_s(s, t) = \frac{\partial v(s, t)}{\partial s}, v_{ss}(s, t) = \frac{\partial^2 v(s, t)}{\partial s^2} \) and the coefficients \( \alpha \) and \( \beta \) control, respectively, the snake’s tension and rigidity.

- The external snake’s energy \( E_{\text{ex}} \) acts on the snake determined from the image gradient. \( \alpha \) and \( \beta \) tend to shrink the curve, whereas \( E_{\text{ex}} \) tends to expand it.

\[
E_{\text{ex}}[v(s, t)] = -P[v(s, t)] \quad (3)
\]

where \( P[v(s, t)] \) is a shape potential.

So the total energy of the snake (1) can be written as:

\[
E_{\text{snake}} = \int_0^1 \left( \frac{\alpha}{2} |v_s(s, t)|^2 + \frac{\beta}{2} |v_{ss}(s, t)|^2 - P[v(s, t)] \right)\,ds \quad (4)
\]

Determination of \( \alpha \) and \( \beta \)

The coefficients \( \alpha \) and \( \beta \) were determined and optimized from the analysis of 30 synthetic images including geometries with shapes close to Doppler echocardiographic velocity signals (triangles and trapezoids). Different values for \( \alpha \) and \( \beta \) were tested to minimize the difference between the real known geometric shape area and the one predicted by the snake method. Following this substudy, the parameters \( \alpha \) and \( \beta \) were set to 0.05 and 0, respectively.

Generalized gradient vector flow field

Original snakes did not solve contour detection problem completely. It was required to place the initial snake close to the real boundary of the object; otherwise the snake did not converge to the correct result. Moreover, if a snake is initiated inside the object, the use of additional forces allowing the expansion of the snake is required (Cohen 1991). This limitation associated with the use of eqn (4) can be overcome by using the generalized gradient vector flow (GGVF) field introduced by Xu and Prince (1998) instead of a potential field. Using GGVF, the snake does not need a previous knowledge about whether to shrink or expand toward the boundary and could be initialized far from this one. The GGVF is defined as the
equilibrium solution of the following vectorial partial differential equation:

$$\frac{\partial v}{\partial t} = g(|V m|)\nabla^2 v - h(|V m|)(v - V m)$$

(5)

where $v$ is the vector field, $g$ and $h$ are weighting functions and $m$ is an edge map derived from the image.

In this study, the two functions $g$ and $h$ were selected such that the computed GGVF field conformed to the edge map gradient $(V m)$ at strong edges but varied smoothly away from boundaries:

$$g(|V m|) = e^{-|V m|/K}, h(|V m|) = 1 - g(|V m|)$$

(6)

where $K$ is a constant, governing the trade-off between the field smoothness and the gradient conformity. $K$ was fixed at 0.25 in this study.

**Initial positioning**

The initial positioning of the snake in our study was determined from the automatic method developed by Tauber et al. (2005) (Figs. 1 and 2). This approach is a generalization of the centers of divergence (CD) introduced by Xingfei and Tian (2002). These centers are the points where the GGVF vectors change one direction (weak divergence) or several directions (strong divergence) (see Figs. 1b and 2b).

Let $\text{sign}(x)$ be a function showing the sign of $x$:

$$\text{sign}(x) = \begin{cases} 1 & x > 0 \\ 0 & x = 0 \\ -1 & x < 0 \end{cases}$$

(7)

Then a set of CD for the vertical direction ($C_v$) and for the horizontal direction ($C_h$) of the vector field $v(i, j) = (a(i, j), b(i, j))$ can be defined as:

$$C_v = \{ (i, j) | a(i, j) \leq a(i + 1, j) \wedge \text{abs} (\text{sign} (a(i, j)) + \text{sign} (a(i + 1, j))) \leq 1 \}$$

$$C_h = \{ (i, j) | b(i, j) \leq b(i, j + 1) \wedge \text{abs} (\text{sign} (b(i, j)) + \text{sign} (b(i, j + 1))) \leq 1 \}$$

(8)

Finally, the following definition for the set of the centers of weak divergence ($C_{\text{weak}}$) and for the set of the centers of strong divergence ($C_{\text{strong}}$) can be introduced:

![Fig. 1. Aortic flow. (a) Initial Doppler echocardiographic image. (b) Generalized gradient vector flow (GGVF) field (yellow vectors). (c) Centers of divergence (blue line), initial positioning and size of the snake (black circle) and the horizontal line allowing initializing the size of the snake (black dashed line).](image-url)
\[
C_{\text{weak}} = \{ (i,j) | (i,j) \in C_v \lor (i,j) \in C_h \} \\
C_{\text{strong}} = \{ (i,j) | (i,j) \in C_v \land (i,j) \in C_h \}
\] (9)

Figures 1c and 2c show two examples of CD calculated from two Doppler echocardiographic images obtained from Sonos 7500 (Philips Medical Systems, Amsterdam, The Netherlands). The centers of weak divergence (in blue on the figure) formed a kind of skeleton of the image, where the intersections are the centers of strong divergence. For the aortic flow, only one point occurs, whereas there are two points for the mitral flow caused by the bi-wave (E and A waves) shape of the velocity profile. These centers of strong divergence were used as initial positions of the snake. For the aortic flow, the initial snake was a circle centered on the center of strong divergence, whereas for the mitral flow, the initial snake was an ellipse including the two centers of strong divergence and centered on the middle of the segment formed by these two centers. Each velocity profile of the 30 Doppler echocardiographic images used in this study was first approximated by simple geometric shapes (triangles and trapezoids) with known area. The initial parameters (the diameter of the circle [for aortic flow] and the lengths of the major and the minor axes of the ellipse [for mitral flow]) were then determined for each image (with simplified geometric shapes) to minimize not only the difference between the real known geometric shape area and the one predicted by the snake method, but also the number of iterations during the computation. For the aortic flow, the initial size of the snake was determined from the length of the horizontal line, including the center of strong divergence, demarcated by the edges of the velocity profile. These edges corresponded to the two points where the sign of the GGVF vectors changed from 1 to –1 (see eqn (5)). The circle diameter was fixed experimentally and set to 1/3 of the length of this horizontal line (Fig. 1c). For the mitral flow, the lengths of the major axis and the minor axis were also fixed experimentally and were set, respectively, to 1.3 times the “horizontal” distance between the two centers of strong divergence and 2.3 times the “vertical” distance between the two centers of strong divergence (Fig. 2c).
Method accuracy

Our active contour model was encoded under MATLAB (The MathWorks, Inc., Natick, MA, USA) and has been first validated on 20 simple geometries with shapes close to Doppler echocardiographic velocity signals (triangles and trapezoids). These simple geometries were integrated into the data of the systolic interval of real echocardiographic images (Fig. 3a, top panel). The objective was to evaluate the performance of the method to correctly identify the contour of these simple geometries located within the Doppler image data. To determine the accuracy of the method, the root-mean-square error (RMSE) of the snake method was calculated. The error was defined as the minimum distance between the point predicted using the snake method and the known initial shape (triangles or trapezoids).

\[
RMSE = \frac{1}{\min(d(x_S - x_I))} \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left[ \min(d(x_S - x_I)) \right]^2}
\]  

(10)

where \(\bar{\text{()}}\) is the mean calculated for all the points of the snake, \(N\) is the number of points of the snake, \(x_S\) is the point of the snake, \(x_I\) are the points of the known shape and \(d(.)\) is the distance between the point of the snake and the points of the known shape.

For each image, the snake segmentation was very close to the real boundary (Fig. 3a, bottom panel). The

Fig. 3. Top panel: (a) Noise-free echocardiographic image in which a triangle has been integrated (black line), with initial snake (circle) plotted in black dashed line; (b) noisy echocardiographic image (same image as in (a) but degraded with a strong Gaussian white noise (mean 0.5, variance 0.2)), with initial snake (circle) plotted in black dashed line. Bottom panel: (a) Final position of the snake (yellow dashed line) for the noise-free image; (b) final position of the snake (yellow dashed line) for the noisy image.
The mean value of RMSE calculated from the 20 images was very small (4% ± 0.8%). This value shows the high accuracy of the method.

In the case of cardiac Doppler, velocity echocardiographic images can contain a strong background noise. To test the background noise sensitivity of the method, we have degraded 20 real echocardiographic images with five different strong Gaussian white noises in which we have integrated triangles or trapezoids. Figure 3b (top panel) shows one of the 20 echocardiographic images corrupted by a strong Gaussian white noise (mean 0.5, variance 0.2). The mean value of RMSE calculated from these 20 images was small (6% ± 1.1%). For each image, the snake segmentation was close to the real boundary (Fig. 3b, bottom panel). So the snake capture range was minimally affected by the background noise.

Patient population

The new method was tested on Doppler echocardiographic images (collected retrospectively) of left ventricular outflow tract and transvalvular flow velocity signals recorded in 30 patients with aortic or mitral stenoses, 20 with normal sinus rhythm and 10 with atrial fibrillation. This study was approved by the local ethics committee and written informed consent was obtained from all patients. For each measurement, the contour of the velocity envelope of three cardiac beats was manually traced by two experienced echocardiographers using Sonos 7500 (Philips Medical Systems) and averaged for patients with normal sinus rhythm. For patients with atrial fibrillation, the contour of the velocity envelope of five cardiac beats was used.

RESULTS

For the conventional manual tracing of the Doppler echocardiographic images, we have analyzed interobserver variability from two observers using Student’s t-test and intra-observer variability from three manual tracings for each observer using a one-way analysis of variance (ANOVA). The results of the interobserver variability and the intra-observer variability for each observer are summarized in Tables 1 and 2, respectively. For all cases, the p-value calculated from Student’s t-test and

| Table 1. Student’s t-test with a confidence level α = 0.01 for Vmax, Vmean and VTI between the two observers (interobserver analysis) |
|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|
|                               | Normal                          | Atrial fibrillation             |                                |                                |                                |                                |                                |
| Mean                           | SD                              | t                               | p-value                        | Mean                           | SD                              | t                               | p-value                        |
| MV                             |                                 |                                 |                                |                                |                                 |                                 |                                |
| Vmax                           | 3.0 ± 0.36                      | –0.36                           | 0.72                           | 6.7 ± 0.03                      | 1.6 ± 0.98                      | –0.14                           | 0.88                           |
| Vmean                          | 3.1 ± 0.25                      | –0.25                           | 0.79                           | 4.1 ± 0.14                      | 1.1 ± 0.10                      | –0.10                           | 0.90                           |
| VTI                            | 3.4 ± 0.18                      | –0.18                           | 0.85                           | 4.6 ± 0.26                      | 1.9 ± 0.26                      | –0.26                           | 0.79                           |
| AV                             |                                 |                                 |                                |                                |                                 |                                 |                                |
| Vmax                           | 1.7 ± 0.20                      | –0.20                           | 0.84                           | 1.5 ± 0.6                       | 0.6 ± 0.08                      | 0.08                            | 0.93                           |
| Vmean                          | 1.8 ± 0.11                      | –0.11                           | 0.92                           | 1.6 ± 0.8                       | 0.8 ± 0.10                      | 0.10                            | 0.92                           |
| VTI                            | 2.5 ± 1.12                      | –1.12                           | 0.91                           | 1.9 ± 1.2                       | 1.2 ± 0.12                      | 0.12                            | 0.91                           |

Mean represents the mean of the absolute relative difference. SD is the standard deviation. t is the t-statistic value.

MV = mitral valve; AV = aortic valve.

| Table 2. One-way ANOVA with a confidence level α = 0.01 for Vmax, Vmean and VTI between the three manual tracings for each observer (intraobserver analysis) |
|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|
|                               | Normal                          | Atrial fibrillation             |                                |                                |                                |                                |
| Mean                           | SD                              | F                               | p-value                        | Mean                           | SD                              | F                               | p-value                        |
| Observer 1                     |                                 |                                |                                |                                |                                 |                                |                                |
| MV                             |                                 |                                |                                |                                |                                 |                                |                                |
| Vmax                           | 2.9 ± 0.9                       | 0.02                            | 0.98                           | 3.2 ± 1.1                       | 0.07                            | 0.93                           |
| Vmean                          | 2.8 ± 1.2                       | 0.02                            | 0.97                           | 4.6 ± 1.9                       | 0.08                            | 0.92                           |
| VTI                            | 3.3 ± 1.6                       | 0.04                            | 0.96                           | 9.6 ± 2.5                       | 0.11                            | 0.89                           |
| AV                             |                                 |                                |                                |                                |                                 |                                |                                |
| Vmax                           | 1.8 ± 0.7                       | 0.03                            | 0.97                           | 1.7 ± 0.9                       | 0.01                            | 0.99                           |
| Vmean                          | 4.4 ± 1.5                       | 0.04                            | 0.96                           | 3.1 ± 1.1                       | 0.01                            | 0.99                           |
| VTI                            | 5.6 ± 2.1                       | 0.03                            | 0.97                           | 3.1 ± 1.5                       | 0.01                            | 0.99                           |
| Observer 2                     |                                 |                                |                                |                                |                                 |                                |                                |
| MV                             |                                 |                                |                                |                                |                                 |                                |                                |
| Vmax                           | 2.5 ± 1.0                       | 0.01                            | 0.99                           | 3.1 ± 1.2                       | 0.03                            | 0.97                           |
| Vmean                          | 1.6 ± 0.5                       | 0.01                            | 0.99                           | 4.4 ± 1.3                       | 0.02                            | 0.98                           |
| VTI                            | 2.5 ± 0.9                       | 0.02                            | 0.98                           | 5.9 ± 0.9                       | 0.00                            | 0.99                           |
| AV                             |                                 |                                |                                |                                |                                 |                                |                                |
| Vmax                           | 1.5 ± 0.6                       | 0.02                            | 0.98                           | 1.8 ± 0.6                       | 0.06                            | 0.94                           |
| Vmean                          | 1.9 ± 0.8                       | 0.03                            | 0.97                           | 2.9 ± 1.1                       | 0.04                            | 0.96                           |
| VTI                            | 1.8 ± 0.5                       | 0.03                            | 0.97                           | 3.8 ± 1.4                       | 0.00                            | 0.99                           |

Mean represents the mean of the absolute relative difference. SD is the standard deviation. F is the F-statistic value.

MV = mitral valve; AV = aortic valve.
the ANOVA was higher than the confidence level ($\alpha = 0.01$), which showed that both the interobserver and intra-observer variability were not significant.

The snake’s evolution is represented in Fig. 4, for the aortic flow (top panel) and the mitral flow (bottom panel). The results obtained with the automatic detection method were first compared with those obtained manually by calculating the area overlapping ratio (OR) as follows:

$$ OR = \frac{2 \times area (C_a \cap C_m)}{area (C_a) + area (C_m)} $$

where $C_a$ is the contour delimited using the automatic method and $C_m$ is the contour delimited manually. Comparison between the two methods seemed to show a very good agreement. For all cases, the mean area OR was higher than 96% (Table 3). To refine the comparison, we focused on three essential variables that are measured routinely using Doppler echocardiography in the clinical setting: the maximum velocity ($V_{\text{max}}$), the mean velocity ($V_{\text{mean}}$) and the velocity-time integral (VTI) which is one of the parameters allowing the determination of the valve effective orifice area (EOA), and thus the severity of a stenotic valve. VTI is the area under the velocity-time curve. To quantify the agreement between the two methods, Bland-Altman plots (Bland and Altman 1986) for the three variables were used (Table 4, Figs. 5 and 6). The bias value between the two methods was small in all cases. For patients with aortic or mitral stenosis and normal sinus

![Fig. 4. Top panel: Aortic flow; bottom panel: mitral flow. (a) Initial positioning and size of the snake (blue dashed line). (b) Evolution of the snake (yellow dashed line for the aortic flow, blue dashed line for the mitral flow). (c) Final position of the snake (yellow dashed line).](image)

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<th>Table 3. Area OR (expressed in %) between automatic method (Auto) and manual tracing (Manual) for each observer</th>
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Average means (observer 1 + observer 2)/2.

MV = mitral valve; AV = aortic valve; AF = atrial fibrillation.
If the CNR was too small (<0.4), the snake continued to grow without stopping at the level of the edges of the expected contour and reached or left the ROI (Fig. 8a). The snake’s expansion stopped automatically when the snake area was equal to the selected ROI area. Figures 8b and 8c show a moderate CNR, about 0.6, and a high CNR, about 2.2. In these two cases, the contrast between the inside and the outside regions of the contour was sufficiently high to allow the snake to reach the edges of the expected contour. Figure 7 shows the variations in Vmax, Vmean and VTI (difference between the results obtained from the automatic method and obtained manually divided by the average) in relation to the CNR of the ROI. The variations remained globally lower than about 10% if the CNR was higher than 0.6, whereas for a value of CNR comprised between 0.4 and 0.6, the variations were between approximately 10% and 20%. This difference between the two methods for a moderate CNR (Fig. 8b) can be explained by the fact that with the automatic method, the snake reached the expected contour only on some parts (the rest of the contour was determined by interpolation by the program), whereas the human observer, knowing the shape of the contour to determine, is able to manually extrapolate the values to replace these missing segments. Below 0.4, as mentioned before, the snake did not reach the real contour and the variations in Vmax, Vmean and VTI were, therefore, labeled as 100%.

In view of these results, we have determined experimentally, from 30 images with a low or moderate CNR (between 0.35 and 0.7), a threshold below which the snake’s expansion was not correct, that the snake did not converge toward the contour of interest. Moreover, to keep the global variations below 10%, the threshold was fixed at a CNR of 0.6.

### DISCUSSION AND CONCLUSIONS

In this study, we have presented and validated a new automatic contour detection method based on active contour models and applied it to Doppler echocardiographic velocity measurements. We have shown that this automatic method was weakly sensitive to background noise contained in the ROI of the image. For validation, data obtained with the new automatic detection method were compared with those obtained by the standard manual Doppler echocardiographic tracing method performed by two experienced echocardiographers. These data consisted on Doppler echocardiographic images of left ventricular outflow tract and transvalvular flow velocity signals recorded in 30 patients with aortic or mitral stenosis, 20 with normal sinus rhythm and 10 with atrial fibrillation. Comparison between the two methods has shown a very good agreement. For all cases,
the mean area OR was higher than 96% (Table 3). Moreover, the Bland-Altman analysis performed on the Vmax, the Vmean and the VTI for patients with aortic or mitral stenosis and normal sinus rhythm or atrial fibrillation showed small bias and acceptable limits of agreement (Table 4). Compared with the results obtained by Greenspan et al. (2005) using a method based on a noise-removal technique and an edge-following technique.

Fig. 5. Bland-Altman plots between the automatic method and the manual method in the case of patients with normal sinus rhythm for Vmax, Vmean and VTI. Xauto and Xhand represent, respectively, the variable X obtained from the automatic method and obtained manually. Average is the sum of Xauto and Xhand divided by 2. MV = mitral valve, AV = aortic valve, AF = atrial fibrillation.
algorithm, the bias of our method was lower and the limits of agreement of our method were higher. For example, for patients with normal sinus rhythm, Greenspan et al. obtained, for the mitral flow, higher bias value (12.1%) and limits of agreement (from −12.0% to 36.2%) for the VTI compared with our method (4.4% and from −4.2% to 13.0%, respectively).

The computation time was short, ~5 s including the selection of the ROI (using a standard computer, Pentium 4, 3.2 GHz, IBM, Armonk, NY, USA). This computation
time was a little bit higher than the one of the framework approach proposed by Zhou et al. (2007) (~1 s to process one image). However, our automatic method was more accurate than the method developed by Zhou et al. (2007), in particular in the case of mitral flow. For example, for patients with normal sinus rhythm, Zhou et al. (2007) obtained a mean area OR of 89.3%, whereas with our automatic method, the mean area OR was equal to 96.8% (see Table 3). Also, the computational time that we obtained was still much lower than the manual measurements. An experienced echocardiographer performs them in ~10–15 s without corrections (that means without erasing some points judged incorrect by the echocardiographer) and in ~15–20 s with corrections. The reduced computational time achieved with a standard computer demonstrates that this new method could be implemented in standard echocardiographic equipment.

In conclusion, we have validated a new automatic method of contour detection for Doppler echocardiographic velocity measurements of the mitral and aortic valve flow velocities. This automatic method seems to be robust and accurate. A minor limitation of this method is the necessity to have a sufficient contrast between the inside and the outside regions of the contour of interest. Below this threshold, the user has to increase manually the contrast between the two zones or to recapture the image with a better contrast (in our study, <3% of images had an insufficient contrast). This detection method applied to Doppler echocardiographic velocity measurements could be useful to reduce intra- and interobserver variabilities and minimize measurement errors, and consequently improve quantification of stenosis severity for clinical decision making. This automatic method could also allow the echocardiographer to realize these measurements within a shorter period of time compared with the standard manual tracing method because this new method could be easily implemented in a standard echocardiographic system.

Fig. 7. Vmax, Vmean and VTI variations (expressed in percentage) in relation to CNR for mitral and aortic flows. Variations are the difference between the results obtained from the automatic method and obtained manually divided by the average.

Fig. 8. Comparison of CNR on three images: (a) Low CNR, (b) moderate CNR and (c) high CNR. The yellow dashed line represents the result obtained with the automatic method and the green dashed line points to the one obtained manually.
REFERENCES


