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Identification of the endocardial borders remains challenging in cardiology. In this paper, we propose a new approach named ‘deformation flow tracking’ which couples the obtained boundary from the previous frame and the extracted edges in the current frame by energy minimization. Firstly, the edges are extracted accurately by an effective threshold selection method. Then, the boundary in the previous frame is driven toward the extracted edges to form a deformation boundary by minimizing the energy between the deformation boundary and extracted edge while keeping the deformation boundary smooth. Deformation thresholds are defined and used to constrain the motions of the boundary points and eliminate outliers effectively. The proposed approach was tested on complete short-axis cine MRI datasets from 5 normal subjects and 5 patients with heart failure (total of 1660 images) randomly chosen from a much larger dataset (100 cases). As it turned out, the proposed approach is efficient and robust for automatic identification of the ventricular endocardial boundary that moves directionally and regularly, which is true in most cases.

Keywords: Magnetic Resonance Imaging, Left Ventricle, Right Ventricle, Threshold Selection, Optical Flow, Deformation Flow.

1. INTRODUCTION

Automatic identification of the ventricular boundary of the heart in cine magnetic resonance images (MRI) is an important issue for intelligent healthcare technology that has drawn more and more attention in different fields. It has been studied for decades yet remains a challenging and clinically important problem. We divide the state of art literatures into three categories: (1) spatial domain methods; (2) statistical methods; and (3) time domain tracking methods. Many spatial domain intensity methods utilize a global threshold to accurately identify the ventricular cavity from images which have well-defined differences in pixel intensity between the blood pool and the myocardium. However, the left ventricle often has papillary muscles and rough trabeculations which are included in the ventricular cavity for clinical measurements of volumes and ejection fractions. This type of methods alone cannot achieve a good segmentation since the trabeculations and papillary muscles are typically the same intensity as the myocardium. Other methods utilizing edge information, e.g., gradient vector flow, level set and active contour, could not achieve good performance either.

Statistical methods make use of prior knowledge from user-defined training sets and have improved accuracy compared to spatial domain intensity methods. However, the accuracy of a statistical method is determined by its manually-defined training set, which requires significant effort and includes variability due to human error. Statistical methods also have poor performance on images from patients with diseases that are not represented in the training set.

Because of heart’s characteristics of motion, tracking methods are perhaps the most efficient methods for segmenting the ventricular endocardium from MRI. These methods “track” a known boundary in the first image frame to subsequent frames based on calculated differences between the images. The tracking method based on optical flow might be the most popular one. Optical flow is used to derive a displacement field between two images by matching pixel intensities between the images. However, optical flow often fails to correctly identify the endocardial boundary of the left ventricle of the heart, especially during instances when large displacements occur between adjacent images or the papillary muscles fuse with the wall.

In this paper, we propose a new tracking method for identifying the ventricular boundary from cine MRI. It couples the tracked boundary with the extracted ventricular edge and forms the heart’s deformation flow which is constrained by a deformation threshold. This constraint removes wrong flows effectively. We tested the proposed methods on complete short-axis cine MRI image stacks from 5 healthy volunteers and 5 patients with heart failure (total of 10 image stacks with 73 image slices in total with...
20 or 30 frames per slice for a total of 1660 images). These test datasets are randomly chosen from a large data set. Experimental results show that the proposed method is significantly better than most of the state of art literatures referenced.

The paper is organized as follows. In Section 2, partial differential equation (PDE) based optical flow method is evaluated to track the boundaries of the ventricles. Its advantages and disadvantages are discussed. The principle of proposed approach is described in Section 3. In Section 4, the practical implementation of the proposed approach is described and Section 5 discusses the validation measures. Both qualitative and quantitative results are presented in Section 6. Conclusion is drawn and future work is discussed in Section 7.

2. PARTIAL DIFFERENTIAL EQUATION BASED OPTICAL FLOW METHOD

The definition of optical flow is formulated as:

$$\nabla I \cdot \vec{v} = -I_t$$

(1)

where $\nabla I = (I_x, I_y)$ is the spatial intensity gradient and $I_t$ is the image intensity derivative, $\vec{v} = (v_x, v_y)$ is the image velocity or optical flow. The partial differential equation (PDE) based method expands Eq. (1) using Taylor series and omit the second order terms. Then formulates the optical flow by the following equation:

$$I_1(x + v_x, y + v_y) \approx I_1(x, y)$$

(2)

where $I_1$ denotes the current image and $I_2$ denotes the next image. From solving the Euler equation, Eq. (2) can be transformed to energy minimization problem.

$$E(v_x, v_y) = \frac{1}{2} \alpha \iint (I_1(x + v_x, y + v_y) - I_1(x, y))^2 dxdy + \frac{1}{2} \iint (\nabla^2 v_x + \nabla^2 v_y) dxdy$$

(3)

where the first integration represents the fidelity term and second integration represents the smoothing term.

We also implemented LK optical flow method for comparison. Although PDE optical flow is slower than LK optical flow, its accuracy is significantly better. Besides, we have tried to combine these two optical flow methods as local estimation by LK method and global optimization by energy minimization. However, the experimental results show that its accuracy is just similar to LK method. Hence, we choose PDE optical flow method as the benchmark of the state of art methods.

Compared to all the state of art referenced methods, the advantages of optical flow methods are:

1. easy to operate by a clinical doctor without the process of labor intensive data training by machine learning methods.
2. Competitive accuracy. One of the goals of this research work is to come up with an efficient method which is superior to optical method in identifying the endocardial borders.

To achieve this goal, we need to know the disadvantages of optical flow first. Then it is possible for us to propose a better method to make up for its deficiency.

Since the optical flow method tracks a known boundary based on the intensity variations in the spatial and time domains, the initialization of the known boundary will be critical. If one of the derivatives, spatial or time, is zero or too small, Eq. (1) will become ill-conditioned. Consequently, the tracked point retains the previous position in the current frame and the error accumulates across the whole tracking process. Figures 1(a and b) show the demonstration of this problem when some boundary points lie in the myocardium tracking errors (mismatch 1) occur. In addition to mismatch 1, mismatch 2 occurs because some boundary points lie in the ventricle. As can be seen, when the boundary points fall into myocardium, the tracking errors tend to be large. So we track a tighter boundary on purpose and the results are shown in (c and d), mismatch 1 can be avoided and mismatch 3 (the same as mismatch 2) still occurs. In Figure 2, we show some problems that usually cannot be avoided no matter what initial boundary is tracked. For the left ventricle, when the papillary muscles fuse with the wall, tracking error (mismatch 2) will occur. For the right ventricle, the same errors (e.g., mismatch 1 in Fig. 2(b)) occur frequently.

From the problems of optical flow results, we see that the image intensity and edge information is not utilized sufficiently, which frequently causes errors that can be easily perceived visually. Due to the diversity and irregularity of the errors, it is also difficult or impossible for optical flow method to incorporate other methods (e.g., shape modelling) to achieve an overall
segmentation improvement. Both level set and active contours are well-known methods that are based on the edge information. However, the extracted edges of the ventricles are usually not complete due to the papillary muscles and rough trabeculations. Consequently, active contours or level set alone could not achieve an acceptable segmentation result. Thus, we propose a completely new approach based on the extracted edge and deformation of the ventricles.

3. PROPOSED DEFORMATION FLOW TRACKING APPROACH

3.1. Principle of Deformation Flow Tracking

Hinted by Eq. (3) and the cubic smoothing spline, we propose the deformation flow tracking method in this section. Eq. (3) tries to minimize the difference between ventricular boundary in the previous image and the current image blindly and it could not guarantee the ventricular boundary is accurate solely from the intensity difference between the two images. To make the ventricular boundary more accurate, we extract the boundary, \( B_{in} \) from the edge of the ventricle in the current frame by minimizing the difference between the previously inputted boundary, \( B_{in-1} \) and the edge, \( B_{in} \) in the current frame.

\[
B_{in}^{def}(j) = \arg\min_{B_{in}^{def}(j)} ||B_{in}^{def}(j) - B_{in}(j)||^2
\]

where \( i \) denotes the index of frame number in the image sequences, \( j \) denotes the index of the corresponding points on respective boundaries and it is determined by the point index of inputted boundary \( B_{in}^{def} \) obtained from the previous frame.

We then define the deformation boundary as \( B_{def} \) and compute it by minimizing its energy function between \( B_{in}^{def} \) and \( B_{def} \).

\[
E(B_{def}) = (1 - \alpha) \int ||B_{in}^{def}(j) - B_{def}(j)||^2 dj + \alpha \int \left( \frac{d^2 B_{def}(j)}{dt^2} \right)^2 dt
\]

where \( \alpha \) is the smoothing factor and its default value is 0.5. Different from optical flow, we define deformation flow to constrain the boundary based on the movement regularity of the heart. So large errors can be avoided or reduced. The deformation flow is defined as follows:

\[
\vec{F}(j) = (x_{def}^{in}(j) - x_{def}^{in}(j), y_{def}^{in}(j) - y_{def}^{in}(j))
\]

where \( (x_{def}^{in}(j), y_{def}^{in}(j)) \) and \( (x_{def}^{in}(j), y_{def}^{in}(j)) \) are the coordinates of the \( j \)th points on the deformation boundary and input boundary respectively.

The center, \( (c_x, c_y) \) of the ventricle is computed as follows. First, the segmented ventricle, \( V_1^d \) is eroded by the following equation with the structuring element \( B = \{(0, 0)\} \).

\[
E_x^d = \{ z \mid B^c \in V_1^d \}
\]

Then the area, \( A \) of the eroded ventricle is computed. If \( A > 10 \), erode the ventricle again by Eq. (7) until \( A \leq 10 \). The left bright pixels belong to the center of the ventricle.

\[
c_x = \frac{1}{N_c} \sum_{i=1}^{N_c} x_i
\]

\[
c_y = \frac{1}{N_c} \sum_{j=1}^{N_c} y_j
\]

where \( N_c \) is the number of the left bright pixels. \( x_i \) and \( y_i \) are the \( x \) coordinate and \( y \) coordinate of the bright pixels respectively. The reason we do not erode the ventricle until \( A = 1 \) is for the practical reasons that exceptions frequently occur due to the irregular shape of the ventricle.

To determine the direction of the deformation flow for left ventricle boundary tracking, the angle between the flow vector and the vertex from the boundary point to the center point is computed by the following equations.

\[
\theta(j) = \cos^{-1} \left( \frac{c_x(j) \times u_{def}(j) + c_y(j) \times v_{def}(j)}{\sqrt{(c_x(j))^2 + (c_y(j))^2} \sqrt{(u_{def}(j))^2 + (v_{def}(j))^2}} \right)
\]

where

\[
c_x(j) = c_x - x_{in}^{in}(j)
\]

\[
c_y(j) = c_x - y_{in}^{in}(j)
\]

\[
u_{def}(j) = y_{def}(j) - y_{in}^{in}(j)
\]

\[
u_{def}(j) = y_{def}(j) - y_{in}^{in}(j)
\]

If \( \theta(j) \leq (\pi/2) \), the deformation flow is defined as inward flow and if \( \theta(j) > (\pi/2) \), the deformation flow is defined as outward flow.

Two facts of the ventricle make deformation flow tracking useful.

(1) The motion of the ventricle can be limited by a general deformation threshold \( T_s \) between adjacent frames.

(2) The motion of the ventricle is directional.

It usually moves inward during the systolic stage and moves outward during the diastolic stage. Thus deformation flow can constrain the motion of the ventricular boundary between two adjacent images more effectively with two deformation thresholds \( T_{in}^d \) and \( T_{out}^d \). The value of the deformation threshold is critical for the performance of deformation flow tracking and it is set based on the computed size of the ventricle on line. For all the experiments conducted in this research work, the two thresholds are computed as follows based on trial and error analysis:

\[
T_{in}^d = \frac{C_s}{5\pi}
\]

\[
T_{out}^d = \frac{C_s}{6\pi}
\]

where \( C_s \) denotes the circumference of the ventricle in the first frame and it is computed as:

\[
C_s = \sum_{j=1}^{N_c-1} \sqrt{(x_{in}^{in}(j+1) - x_{in}^{in}(j))^2 + (y_{in}^{in}(j+1) - y_{in}^{in}(j))^2}
\]

where \( N_c \) denotes the number of points on the first inputted boundary \( B_{in}^d \) and \( j \) denotes the index of the points.

Figure 3 shows the process of how the deformation flow couples the inputted boundary with the extracted edge. The inputted boundary of the previous frame is denoted in red and detected boundary (extracted edge) is denoted in blue. As can be seen, there are two large mismatches caused by the inaccurately extracted edges. The deformation flow force which are denoted in blue drives the point of inputted boundary to the nearest edge point and forms the tracked deformation boundary which is denoted in blue. All the large deformation flows are removed by the flow threshold, \( T_{in}^d \) and \( T_{out}^d \).
difference distribution as follows: we calculate the variations of the histogram distribution by slope is the threshold point between two gray-level distributions. Thus, the greatest variation position of the histogram distribution usually to be very effective in segmenting MR images. segmenting fuzzy laser lines and it is also proved in this paper method. Unfortunately, neither of them works well. Hence, we many different images. We implemented the most popular state challenging part changes to find the optimum threshold for so method. The deformation flow force drive the obtained boundary from the previous frame toward the extracted edge, $R_x$, in the current frame. Hence, it is critical to obtain accurate edge of the ventricle. Because direct edge detection methods produce much more edges than that of the ventricle and it is difficult for automatic clustering with the desired accuracy. Similarly, the well-known graphcut methods are inclined to be trapped into undesirable minimum cuts and their segmentation results are not accurate enough for subsequent processing. We use the popular and convenient normalized cut to segment some left venticles and show the results in Figures 4(a-h). As can be seen, the results are not satisfactory. The extracted edges from these segmentation results could not be used for subsequent processing. From original images, we can see obvious contrast between the ventricular areas and the myocardial areas. The failure of the Graphcuts methods was caused by the fuzziness of the image. On the contrary, threshold selection method has better immunity to fuzziness and thus becomes a better choice in this study.

The image can be binarized with the selected threshold and then the edge of the ventricle can be extracted. Thus the most challenging part changes to find the optimum threshold for so many different images. We implemented the most popular state of art threshold selection methods: Otsu’s method and entropy method. Unfortunately, neither of them works well. Hence, we modified the previously proposed threshold selection method in segmenting fuzzy laser lines and it is also proved in this paper to be very effective in segmenting MR images.

The modified threshold method is based on the fact that the greatest variation position of the histogram distribution usually is the threshold point between two gray-level distributions. Thus, we calculate the variations of the histogram distribution by slope difference distribution as follows:

Step 1: Select a region of interests (ROI) around the ventricle and smooth the ROI with the following Gaussian weighted kernel moving filter:

$$h(x, y) = \frac{1}{\sigma \sqrt{2\pi}} \exp \left(-\frac{(x - \mu_x)^2 + (y - \mu_y)^2}{2\sigma^2}\right)$$  \hspace{1cm} (18)

Step 2: Re-arrange the gray-scales in $[1, 255]$. Compute the normalized histogram distribution $P(x)$ of the ROI:

$$P(x = i) = \frac{N_i}{N_j}; \quad i = 1, \ldots, 255$$  \hspace{1cm} (19)

$$j = \arg\max_{j \in [1, 255]} N_j$$  \hspace{1cm} (20)

where $N_i$ denotes the frequency of the gray-scale $i$ and $N_j$ denotes the maximum frequency which occurs at $j$ in the interval $[1, 255]$.

Step 3: Transform $P(x)$ by the Discrete Fourier Transform (DFT):

$$F(k) = \sum_{x=1}^{255} P(x)e^{-i(2\pi k x / 255)}; \quad k = 1, \ldots, 255$$  \hspace{1cm} (21)

$k$ is chosen based on testing on a variety of images. Transform from the frequency domain back into space-time domain by the following equation.

$$P'(x) = \frac{1}{T} \sum_{k=1}^{255} F'(k)e^{i(2\pi k x / 255)}; \quad x = 1, \ldots, 255$$  \hspace{1cm} (23)

$P'(x)$ is the smoothed histogram distribution.

Step 4: Choose the low frequency parts and eliminate the high frequency parts by the following equation.

$$F'(k) = \begin{cases} F(k); & k = 1, 2, \ldots, 10 \\ F(k); & k = 246, \ldots, 254, 255 \\ 0; & k = 11, \ldots, 245 \end{cases}$$  \hspace{1cm} (22)

Step 5: For each point on the smoothed histogram distribution, there are two slopes, one on the left and the other on the right. We compute them by fitting a line model with 15 adjacent points at each side. We tested all the reasonable numbers from 3 to 81 on a variety of images and found that the numbers from 7 to 21 are the most effective parameters for the histogram range from 1 to 255. So we choose 15 for all the experiments. The line model is formulated as:

$$y_i = ax_i + b$$  \hspace{1cm} (24)

$$[a, b]^T = (B^TB)^{-1}B^T Y$$  \hspace{1cm} (25)

$$B = \begin{bmatrix} x_1 & 1 \\ x_2 & 1 \\ \vdots & \vdots \\ x_{15} & 1 \end{bmatrix}$$  \hspace{1cm} (26)

$$Y = [y_1, y_2, \ldots, y_{15}]^T$$  \hspace{1cm} (27)

Two slopes at point $i$, $a_i(i)$ and $a_{16}(i)$, are then obtained from Eq. (24).

Step 6: Compute the slope difference, $s(i)$, at point $i$:

$$s(i) = a_{16}(i) - a_i(i); \quad i = 16, \ldots, 240$$  \hspace{1cm} (28)

Set the derivative of $s(x)$ to zero.

$$\frac{ds(x)}{dx} = 0$$  \hspace{1cm} (29)
Solving the above equation, we get the valleys $V_i; i = 1, \ldots, N_v$ of the slope difference distribution. We choose the position where the valley $V_i$ has the maximum absolute value as the candidate threshold point.

**Step 7:** Compute the mean value of the image as:

$$T_w = \frac{1}{N_T} \sum_{i=1}^{255} i \times N_i$$  \hfill (30)
Fig. 5. Comparison of the proposed method with state of art methods on a normal case Slice 6, Frame 1. (a) Original image; (b) threshold selection process; (c) segmentation result with the threshold, 62 by proposed method; (d) segmentation result with the threshold, 72.4 by image mean method; (e) segmentation result with the threshold, 107 by Otsu's method; (f) segmentation result with the threshold, 95 by entropy method.

Where $N_f$ denotes the total number of pixels contained in the image.

**Step 8:** Find the nearest valley $V_i$ to $T_m$ and choose this valley position as the optimum threshold. We choose the mean value of the image as a benchmark to select the threshold because the ROI is selected as nearly twice or less of the size of the ventricle and the average value of the ventricle intensity is close to the image mean.

We choose a typical image (Fig. 5(a)) from the test database (60 Tetralogy of Fallot (TOF) patient cases and 40 normal cases) and show the visual comparison between the proposed method and state of art threshold selection methods. As can be seen, the proposed method can segment the ventricle more completely than other state of art methods for this clear image. For the fuzzy image (Fig. 6(a)), all methods fail to segment the ventricle from the myocardium due to fuzziness between them. The fuzziness of the image can be distinguished by its histogram distribution as shown in Figures 5–6(b) by the red line. The clear image always has one distinguished peak from other parts while the fuzzy image has no distinguishable peaks and its histogram tends to be equalized. For the fuzzy image, the fuzziness accumulates with its size because its histogram is affected by the total number of fuzzy pixels. To decrease the fuzziness effect, we select a slice from the ROI and apply the threshold selection again based on the slice. As expected, the threshold computed from the slice is more accurate than that computed from the whole ROI. We show
Fig. 6. Comparison of the proposed method with state of art methods on a patient case Slice 6, Frame 1. (a) Original image; (b) threshold selection process; (c) segmentation result with the threshold, 119 by proposed method; (d) segmentation result with the threshold, 115.5 by image mean method. (e) Segmentation result with the threshold, 115 by Otsu’s method; (f) segmentation result with the threshold, 118 by entropy method.

the segmentation results in Figure 7. As can be seen, the ventricle is separated from the myocardium successfully. The selection of the slice is based on the computed center of the ventricle by Eqs. (8) and (9) on a frame by frame basis.

For the demonstration of the threshold selection process in Figures 7–9, the blue line denotes the original histogram distribution and the red line denotes the smoothed histogram probability distribution. The red brown denotes the slope differences that are originally smaller than zero and are reversed to be greater than zero with a minor sign. The green line denotes the derivatives of the slope differences and the blue circles denote the valleys of the slope differences.

After the optimum threshold is selected, we use it to binarize the image and then use a mask to eliminate outliers. The mask is defined as follows.

From the first inputted boundary $B^i_1$, we obtain a binarized ventricle, $V^b_1$ and then we dilate it until it touches the boundary of the ROI by the following equation.

$$M^i_1 = V^b_1 \oplus B = \{ z \mid (B^i), \cap V^b_1 \neq \emptyset \}$$

where $B = \{(0,0)\}$ and $B^i$ denotes the symmetric or supplement of $B$. $M^i_1$ is the binarized mask whose area covers the ventricles for all the images in the same slice. We use this mask to eliminate all the outliers that lie outside the dilated ventricle and then the binarized ventricle can be easily selected based on the
size the binarized blobs (the one with the largest size). At last, the edge of the ventricle is extracted by subtracting the original binarized ventricle with the morphologically eroded one with the structuring element \( B \).

### 4. IMPLEMENTATION OF THE APPROACH

This section describes the practical steps of implementing the proposed approach to identify the ventricular boundary. Similar to optical flow method, the first boundary \( B_{in}^1 \) is computed independently in the first frame of the slice. In our experiments, level set method is used to calculate the first boundary. Then the boundaries in all the other frames are computed by the proposed approach. With the first boundary, \( B_{in}^1 \) known, the following steps are repeated:

**Step 1:** An optimum threshold \( T_{opt} \) is computed by the threshold selection method.

**Step 2:** The edge of binarized ventricle is extracted and denoted as \( B_{ex}^i \).

**Step 3:** The deformation flow between the extracted edge \( B_{ex}^i \) and the inputted boundary \( B_{in}^{i-1} \) from the previous image is computed. Then boundary points of \( B_{in}^{i-1} \) are moved according to the computed deformation flow to form a new boundary \( B_{def}^i \), which is then used as the input boundary to process the next image.

**Step 4:** Repeat steps 2–3 until all the boundaries are identified. Similar to optical flow method, we compute the deformation flow starting from frame 1 both backward and forward. The forward propagation is stopped at 40% of the length of the cardiac cycle which is the approximate location of the end-systolic frame where the ventricle is the smallest. Figure 8 shows an example of a slice with a total of 20 images and the forward propagation stops at frame 8. Figure 9 shows the block diagram of the proposed approach when it tracks forward.

### 5. VALIDATION METHOD

Two quantitative measures are used to evaluate the performance of the proposed approach versus optical flow method:

1. volume agreement between the manual (segmentation by the practitioner) and automatically computed boundaries assessed by Dice metric similarity measure; and
2. mean absolute distance (MAD) between the manual and automatically calculated boundaries.

Typically, a MR image volume contains about 10 image slices which contain 20 or 30 image frames. To compute Dice measure, the image slices from an individual patient or normal subject are stacked to form a 3D volume. Let \( V_n \) represent the volume of the
manually segmented ventricle. $V$ represents the volume identified by the proposed method or by the optical flow method. Then the Dice is computed as:

$$\text{Dice} = \frac{2|V \cap V'|}{|V| + |V'|}$$  \hspace{1cm} (32)

To define the MAD, the end-diastolic and end-systolic ventricle with the largest and smallest size are detected respectively. Then $M_s$ points on the largest ventricle boundary are selected based on its circumference $c_s$. Suppose $M_s = c_s/2$, then the error was quantified roughly every 2 pixels. A correspondence trajectory is drawn between each sampled point and the centroid of the smallest ventricle boundary using a mapping defined by the gradient field of the solution of the Laplace equation.\(^{37}\) To make sure that the correspondence trajectories can intersect all the segmented boundaries in the same slice, it is extended outward from the sampled points based on the slope of the trajectory at the sampled points. The intersections of the trajectories with the tracked boundaries are denoted as $(P^i_{m, s, f})$ and the intersections with the manual boundaries identified by medical expert are denoted as $(P^p_{m, s, f})$, where $i$ denotes the index of the sampled points, $f$ denotes the image index in each slice and its maximum number $N_s$ is either 20 or 30, $s$ denotes the slice index. The MAD is defined as:

$$\text{MAD} = \frac{1}{M_s \times 20 \times (s_2 - s_1)} \sum_{i=1}^{M_s} \sum_{f=1}^{N_s} \sum_{m=1}^{s_2} |P^i_{m, s, f} - P^p_{m, s, f}|$$  \hspace{1cm} (33)

Figure 10 shows the plotted trajectories for one slice and intersection points for one frame both with the tracked boundary and the manual boundary. The blue circle denotes points on the tracked boundary and the green cross denotes the points on the manual boundary.

6. RESULTS

A large data set of cardiac magnetic resonance images (MRI) were obtained from patients with heart failure and from healthy volunteers with no history of cardiac disease. Steady-state free precession (SSFP) short-axis cine images were acquired during 10–15 second breath-holds with a 1.5T Philips Intera scanner using a 5-element phased array cardiac coil (Philips Medical Systems, Best, Netherlands). Contiguous 8–10 mm slices were acquired at 20 or 30 frames per cardiac cycle. Acquisition parameters were as follows: acquired matrix size $= 192 \times 256$, reconstructed matrix size $= 256 \times 256$, field of view (FOV) $= 370$ mm, flip angle $= 65^\circ$, TR $= 4$ msec and TE $= 2$ msec. Five normal cases and five patient cases are randomly chosen from the large data set with MATLAB function Randi. A total of 10 image stacks with 73 image slices in total with 20 or 30 frames per slice for a total of 1660 images were used for quantitative analysis. The number of used images is greater than those used in most references. In addition, both the proposed method and the optical flow do not rely on the training sets and solely utilize the image intensity and heart movement that are common features for all subjects.

Firstly, we show more qualitative results by the modified threshold selection method to compare with other state of art threshold selection methods in Figures 11–15. From these visual comparisons, it is seen that the overall performace of the proposed threshold selection method is significantly better than the state of art threshold selection methods in segmenting the ventricle to be as complete and accurate as possible.

The worst tracking results by the proposed approach and PDE optical flow are shown in Figure 16. The 8th frame (usually largest errors occur in this frame after accumulation backward or forward) of the central slice of each case is selected and shown for visual comparison between the proposed approach and PDE optical flow method or other state of art methods. The image on the left shows the inputted boundary in the first frame of the slice; The image in the center shows the tracked results by optical flow and the image on the right shows the tracked results by deformation flow. As can be seen, in (a–g), the proposed approach are good in identifying the ventricular borders, especially for the left ventricles. In (h), the patient case does not follow the regular movement that includes outspreading during diastolic stage and
contracting during systolic stage, which causes the poor performance of the deformation flow tracking. However, such kind of cases is very few.

A total of 10 image stacks with 73 image slices in total with 20 or 30 frames per slice for a total of 1660 images were used for quantitative analysis. Table I shows the comparison of the proposed approach with state of the art methods and PDE optical flow method that has been frequently used as the benchmark by the state of art literatures. As can be seen, the proposed approach performs better than both PDE optical flow in indentifying the left ventricular boundaries. Although PDE optical flow performs a litter bit better in indentifying the right ventricular boundaries, the difference is insignificant. On the contrary, the proposed approach performs significantly better than PDE optical flow in identifying the left ventricles. Compared to state of the art methods, the overall accuracy of the proposed approach is also superior.

7. DISCUSSION

The major contributions of this study includes:

(1) A new tracking approach named as ‘deformation flow tracking’ is proposed to robustly and efficiently identify the ventricular endocardial boundary of the MR heart that follows regular movement: outspreading during diastolic stage and contracting during systolic stage.
(2) The slope difference distribution based threshold selection method previously proposed in Ref. [35] was modified, improved and used in this research work. It is indespensable for the proposed approach to achieve high accuracy because this threshold selection method breaks through the bottleneck of segmentation accuracy as stated and testified in Refs. [36, 37].

We compare the proposed approach with state of the art methods in the three main categories:

(1) spatial domain methods;
(2) statistical methods; and
(3) time domain tracking related methods.

7.1. Comparison with Spatial Domain Methods

In Ref. [2], Otsu’s algorithm is used for segmenting the LV and was found to have a volume similarity rate of 85.5% compared to a rate of 95.6% in this study. In Ref. [4], Expectation maximization (EM) thresholding is used to segment the LV from cine MR images. The authors reported a MAD of 1 pixel (compared to 0.6 pixels in this study).

In Ref. [1], the authors utilize iterative thresholding to segment the left ventricle. Unfortunately, the authors only used Bland-Altman limits of agreement of ventricular end-systolic and end-diastolic volumes to validate their results, so we cannot compare our quantitative results to theirs directly. However, we note that ventricular volumes are an extremely rough measure of accuracy.
7.2. Comparison with Statistical Methods

Statistical methods model the motion of the heart over time to utilize the temporal information in the image sequences. This motion modeling relies heavily on manually-defined “training sets” and therefore may lack generality. In Ref. [8], active appearance models (AAM) and active shape models (ASM) are combined to segment the left ventricle. The reported MAD is 1.43 mm for endocardium and 1.51 mm for epicardium compared to 0.77 mm for endocardium in our study. In Ref. [9], a multistage hybrid appearance model methodology based on AAM and ASM is presented to segment both the left and right ventricles. The reported RMS, which is nearly identical to MAD, is 1.71 mm for LV endocardium compared to 0.77 mm in this study. In Ref. [10], a combination of ASM and AAM was used to segment the ventricles. The reported MAD is 1.67 mm for normal endocardium, 1.81 mm for normal epicardium, 1.71 mm for patient endocardium and 1.97 mm for patient epicardium compared to the average 0.77 mm for normal endocardium and patient endocardium in this study.

In Ref. [11], active appearance motion models (AAMM) are used to segment the LV. The reported MAD by AAMM is
Comparisons of threshold selection methods on a patient case Slice 6, Frame 1. (a) Original image; (b) threshold selection process; (c) segmentation with threshold, 59 by proposed method; (d) segmentation with threshold, 98.2 by image mean. (e) Segmentation with threshold, 109 by Otsu’s method; (f) segmentation with threshold, 117 by entropy method.

0.63 mm compared to 0.77 mm in this study. In Ref. [13], a subject-specific dynamical model (SSDM) is developed. The reported MAD is 0.69 mm for 22 healthy human images compared to 0.77 mm for 5 normals and 5 patients in this study. These are the only two referenced LV papers that reported better quantitative results. However, in Ref. [13], the authors did not address patient cases which are more challenging and most relevant to clinical practice. In addition, they use a different validation measure which may account for their slightly better quantitative results. Most important of all, the authors reported results based on only 1 normal subject while using the other 21 normal subjects for training. In Ref. [12], the authors also reported the MAD by AAMM as 1.42 mm while the reported MAD by AAMM in Ref. [11] was much better at 0.63 mm. This discrepancy suggests that the machine learning methods AAMM and SSDM may lack generality and their accuracy is highly dependent on the training sets. As reported in Ref. [12], the AAMM contour detection method failed entirely on 3 of 20 studies which were then excluded from analysis. On the contrary, the proposed method never completely fails to define an ventricular boundary. Deformation flow has the advantage of realistically constraining the motion of the ventricular boundary without using manually-defined training sets.

7.3. Comparison with Time Domain Tracking Methods
In Ref. [27], incompressibility of the myocardium is used to constrain all the frames. The authors reported a lower true positive rate of 91.4% compared to the rate of 95.6% in this study.
Fig. 15. Comparisons of threshold selection methods on a patient case Slice 6, Frame 8. (a) Original image; (b) threshold selection process; (c) selected center slice from the ROI; (d) detected slope difference valleys on the histogram distribution; (e) segmentation with threshold, 121 by proposed method; (f) segmentation with threshold, 103.5 by image mean. (g) Segmentation with threshold, 108 by Otsu’s method; (h) segmentation result with the threshold, 125 by entropy method.
Similarly, MAD was larger at 1.71 mm compared to the MAD of 0.77 mm in this study. In Ref. [28], prediction based collaborative trackers (PCT) are presented to segment ultrasound and CT images. The authors report MAD of 1.28 mm compared to an MAD of 0.77 mm for the proposed. In Ref. [29], a tracking approach based on multiple models is introduced and the authors use root mean squared error (RMSE), which is similar to MAD, to evaluate their method quantitatively. The reported
RMSE is 1.5 pixels (2.0 mm) compared to 0.77 mm for the proposed.

8. CONCLUSION

In this paper, a new approach is proposed to automatically identify the boundary of the ventricular boundaries from cine MR images. It is based on the regularity of the heart’s deformation and couples on-line updated boundary of the previous frame to the extracted ventricle edge in the current frame by energy minimization. The proposed new approach is based on significant improvement of segmentation accuracy achieved by improving the previously proposed threshold selection method that is significantly more accurate than state of art methods. Experimental results verified that this new approach is more efficient and robust in identifying the ventricular boundaries compared to state of art literatures.

The future work includes, but not limited to:
1. verify the proposed approach further using open access datasets;
2. combine the proposed approach with PDE optical flow to segment the ventricular boundaries for higher accuracy;
3. generalize the proposed approach to other video processing applications.

References and Notes