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Dynamic Directional Gradient Vector Flow for Snakes

Jierong Cheng and Say Wei Foo

Abstract—Snakes, or *active contour models*, have been widely used in image segmentation. However, most present snake models do not discern between positive and negative step edges. In this paper, a new type of dynamic external force for snakes named *dynamic directional gradient vector flow (DDGVF)* is proposed that uses this information for better performance. It makes use of the gradients in both x and y directions and deals with the external force field for the two directions separately. In snake deformation, the DDGVF field is utilized dynamically according to the orientation of snake in each iteration. Experimental results demonstrate that the DDGVF snake provides a much better segmentation than GVF snake in situations when edges of different directions are present which pose confusion for segmentation.

Index Terms—Boundary detection, directional gradient, gradient vector flow (GVF), snake.

I. INTRODUCTION

SNAKES, or *active contour models*, was first proposed by Kass *et al.* in 1987. Since its publication [1], deformable models have become one of the most active and successful research areas in image segmentation [2].

Deformable models are curves or surfaces defined within an image domain that move under the influence of internal forces and external forces. Internal forces, which are defined within the curve or surface itself, are designed to smooth the model during deformation. External forces, which are computed from the image data, are defined to move the model toward desired features in the image. Hence, deformable models are able to incorporate different information about the object shape, according to different applications.

There are basically two types of deformable models: parametric deformable models [1], [3], [4] and geometric deformable models [5], [6]. Parametric deformable models represent curves and surfaces explicitly in their parametric forms while geometric deformable models represent curves and surfaces implicitly as a level set of higher dimensional scalar function [7], [8]. Compared with parametric deformable models, geometric deformable models are able to handle topological changes naturally. However, more attention has been paid to the former, as topological adaption is not always required, for example, when applied to medical images with noise.

For parametric deformable models, snakes are widely applied in boundary detection, shape modeling, motion tracking,

etc. Various improvement of snakes has been proposed for different applications. Some are proposed to change the topology of snakes [9], and others are to extend the model to higher dimension data [10] and color images [11]. However, most of the methods are concerned with the external energy in the snake model, such as balloons [3], distance potential force [12], diffusion snakes [13], gradient vector flow (GVF) [14], its generalization (GGVF) [15], and improvement [16]–[18].

The value of gradient is an important information for image processing and analysis. On the problem of the direction of gradient, Park *et al.* proposed a method to improve the active contour model by including gradient direction in the external image force [19]. In order to consider the directional information of the gradient, the angle between the gradient direction and the contour's normal direction at each snaxel (snake elements) is calculated. If the abstract angle is larger than $\pi/2$, the external force at the corresponding snaxel is set to zero. In this case, the directional snake does not get attracted to the edges with an opposite direction to the gradient direction. Thus, only the edges with a desired gradient direction participate in the snake deformation. However, this new definition of the external force highly depends on the initial location of the snake in the image. In the efficient energies and algorithms for parametric snakes [20], the gradient direction is taken into account by the new edge-based energy, which uses the gradient vector field in the integral directly instead of a scalar field derived from the magnitude of the gradient vector field. This method also requires that the snake be initialized very close to the desired boundary.

In this paper, a new type of dynamic external force for snakes is proposed. Based on GVF [14], our external force model endows the snake with a large capture range and the ability to move into boundary cavities. By incorporating directional gradient information, the snake is able to discern edges of different orientations. This is particularly useful for boundary detection of certain classes of images as illustrated in the later part of this paper.

This paper is organized as follows. In the next section, a revision of the traditional snake and the GVF snake is given. The proposed dynamic directional GVF (DDGVF) algorithm is described in detail in Section III. In Section IV, a comparison of DDGVF with the directional GVF (DGVF) proposed by Tang *et al.* [18] is given. The performance of the method is presented in Section V and the conclusion is drawn in Section VI.

II. BACKGROUND

A. Traditional Snakes

A snake is a curve $\mathbf{x}(s) = [x(s), y(s)]$, $s \in [0, 1]$, which moves through the spatial domain of an image to minimize the

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Fig. 1. (a) The 100×100 -pixel binary image of step edges. (b) Edge map of GVF: gradient magnitude. (c)–(d) GVF field in the x and y direction, respectively, (before normalized with respect to their magnitudes).

following energy function:

$$E(\mathbf{x}) = \int_0^1 \left[\frac{1}{2} \left(\alpha \left| \frac{\partial \mathbf{x}}{\partial s} \right|^2 + \beta \left| \frac{\partial^2 \mathbf{x}}{\partial s^2} \right|^2 \right) + E_{\text{ext}}(\mathbf{x}) \right] ds \quad (1)$$

where α and β are the weights controlling the snake's tension and rigidity, respectively. The first-order derivative $\partial \mathbf{x} / \partial s$ controls stretching and the second-order derivative $\partial^2 \mathbf{x} / \partial s^2$ controls bending. The first two terms comprise the internal energy of the snake. The external energy E_{ext} is derived from the image and set to small values at the features of interest. As the gradients at the object boundaries in the image are usually high, external energy of the form $-|\nabla(G_\sigma(x, y) * I(x, y))|^2$ is used for step edges [1] and $\pm G_\sigma(x, y) * I(x, y)$ for line-drawings, where G_σ is a two-dimensional (2-D) Gaussian function with standard deviation σ .

To minimize $E(x)$, the deformable contour has to evolve dynamically as a function of time t given by

$$\gamma \frac{\partial \mathbf{x}}{\partial t} = \frac{\partial}{\partial s} \left(\alpha \frac{\partial \mathbf{x}}{\partial s} \right) - \frac{\partial^2}{\partial s^2} \left(\beta \frac{\partial^2 \mathbf{x}}{\partial s^2} \right) + F_{\text{ext}}(\mathbf{x}). \quad (2)$$

On the right side of the equation, the first two terms are the internal force shrinking and smoothing the contour while the external force $F_{\text{ext}}(\mathbf{x}) = -\nabla E_{\text{ext}}(\mathbf{x})$ pulls the contour to the desired features in the image, e.g., object boundaries.

There are two key drawbacks associated with snakes introduced by Kass *et al.* [1]. First, the initial position of the snake must be close enough to the desired contour in the image. Otherwise the snake may be trapped in local minima instead of evolving correctly toward the desired contour. Second, poor convergence may result as the snake has difficulty evolving to concavities or sharp corners.

B. GVF Snakes

To solve the problem of limited capture range and poor convergence, Xu and Prince proposed GVF as a new external force for snakes [14], [21]. Starting from (2), the external force $-\nabla E_{\text{ext}}(\mathbf{x})$ is replaced with a GVF field $\mathbf{v}(x, y) = [u(x, y), v(x, y)]$ defined as the equilibrium solution of the following system of partial differential equations:

$$\mathbf{v}_t = \mu \nabla^2 \mathbf{v} - (\mathbf{v} - \nabla f) |\nabla f|^2, \quad \mathbf{v}_0 = \nabla f \quad (3)$$

where $\mathbf{v}_t$ denotes the partial derivative of $\mathbf{v}$ with respect to t , and $\nabla^2 = \partial^2 / \partial x^2 + \partial^2 / \partial y^2$ is the Laplacian operator. f is an edge map derived from the image and defined to have larger values at the features of interest. A typical choice is given as follows:

$$f(x, y) = -E_{\text{ext}}(x, y) = |\nabla(G_\sigma(x, y) * I(x, y))|^2 \quad (4)$$

for step edges or

$$f(x, y) = -E_{\text{ext}}(x, y) = -G_\sigma(x, y) * I(x, y) \quad (5)$$

for line-drawings (black on white). An example of GVF edge map and field is shown in Fig. 1.

When $|\nabla f|$ is small, the solution of (3) is dominated by $\mathbf{v}_t = \mu \nabla^2 \mathbf{v}$, which implies homogeneous linear diffusion yielding a slowly varying field of $\mathbf{v}$. Whereas when $|\nabla f|$ is large, the second term in (3) is dominant and produces the effect of keeping $\mathbf{v}$ nearly equal to ∇f . The parameter μ regulates the tradeoff between the first term and the second term in the equation and should be set according to the amount of noise present in the image (larger μ for higher noise).

As the GVF field is calculated as a diffusion of the gradient vectors of a gray-level or binary edge map derived from the image, it greatly increases the capture range of the snake and its capability to move into boundary concavities.

III. DDGVF

In snakes, the role of external force is to attract the deformable contour to the features of interest in the image. Both traditional snakes and GVF snakes define external energy to be a function of $|\nabla I|$, the gradient magnitude of the image, which is a conventional step edge detector. As the magnitude operator discards the signs of gradient, the snake is unable to distinguish between positive and negative step edge. To deal with this problem, we propose the DDGVF to distinguish between positive boundary and negative boundary. For gray-level images, a boundary is defined to be positive if there are positive step edges along its outward normals, i.e., the intensity gradients along the boundary are pointing inward. Contrarily, a boundary is defined to be negative if there are negative step edges along its outward normals.

Fig. 2. Detection of positive and negative step edges.

A. Directional Edge Map

As presented above, the solution of GVF field is based on the edge map f in (4). In the proposed method, a new edge map is used to preserve the gradient directional information

$$g(x, y) = \nabla(G_\sigma(x, y) * I(x, y)) = (g_x(x, y), g_y(x, y)) \quad (6)$$

where g_x and g_y are the horizontal and vertical gradients of the image I after it is smoothed by a 2-D Gaussian function G_σ . Subsequently, the DDGVF field is solved in the horizontal and vertical directions separately.

Consider a one-dimensional signal s depicted in Fig. 2. There are two opposite directions to look through it: x and $-x$. In the x direction, d_1 is a positive step edge and d_2 is a negative step edge. While in the $-x$ direction the situation is reversed: d_2 is a positive step edge and d_1 is negative. Thus, if only positive (or negative) edges are to be detected, the result will depend on the direction of approach. $\max\{s_x, 0\}$ keeps the positive step edges in the x direction and $-\min\{s_x, 0\}$ keeps the positive step edges in the $-x$ direction. As for negative step edges, $-\min\{s_x, 0\}$ is for the x direction and $\max\{s_x, 0\}$ for the $-x$ direction.

Similarly, in the 2-D case, detection of a positive (or negative) boundary is dependent on the direction of approach that associates with the deformable contour's normal direction at each snaxel. Since the location of snake is unknown before initialization, image gradients from all directions are considered. For a positive boundary

$$f_x^+(x, y) = \max\{g_x(x, y), 0\} \quad (7a)$$

$$f_x^-(x, y) = -\min\{g_x(x, y), 0\} \quad (7b)$$

$$f_y^+(x, y) = \max\{g_y(x, y), 0\} \quad (7c)$$

$$f_y^-(x, y) = -\min\{g_y(x, y), 0\} \quad (7d)$$

and for a negative boundary

$$f_x^+(x, y) = -\min\{g_x(x, y), 0\} \quad (8a)$$

$$f_x^-(x, y) = \max\{g_x(x, y), 0\} \quad (8b)$$

$$f_y^+(x, y) = -\min\{g_y(x, y), 0\} \quad (8c)$$

$$f_y^-(x, y) = \max\{g_y(x, y), 0\} \quad (8d)$$

where f_x^+ , f_x^- , f_y^+ , and f_y^- are the gradients of positive step edges in x , $-x$, y , and $-y$ directions, and they make the directional edge map $\mathbf{f}(x, y) = [f_x^+(x, y), f_x^-(x, y), f_y^+(x, y), f_y^-(x, y)]$.

For line-drawings, the directional edge map can be computed using (5)

$$f_x^+(x, y) = f_x^-(x, y) = f_y^+(x, y) = f_y^-(x, y) = -G_\sigma(x, y) * I(x, y). \quad (9)$$

B. Dynamic Directional GVF Field

The DDGVF field has four components: $\mathbf{v}(x, y) = [u^+(x, y), u^-(x, y), v^+(x, y), v^-(x, y)]$ for four directions. These components are found by solving the following partial differential equations:

$$\mathbf{v}_t = \mu \nabla^2 \mathbf{v} - (\mathbf{v} - \mathbf{df}) \mathbf{df}^2, \quad \mathbf{v}_0 = \mathbf{df} \quad (10)$$

where $\mathbf{df} = [df_x^+, df_x^-, df_y^+, df_y^-]$, and

$$df_x^+ = \frac{\partial}{\partial x} f_x^+ \quad (11a)$$

$$df_x^- = \frac{\partial}{\partial x} f_x^- \quad (11b)$$

$$df_y^+ = \frac{\partial}{\partial y} f_y^+ \quad (11c)$$

$$df_y^- = \frac{\partial}{\partial y} f_y^-. \quad (11d)$$

Equation (10) can be rewritten as

$$u_t^+ = \mu \nabla^2 u^+ - (u^+ - df_x^+)(df_x^+)^2, \quad u_0^+ = df_x^+ \quad (12a)$$

$$u_t^- = \mu \nabla^2 u^- - (u^- - df_x^-)(df_x^-)^2, \quad u_0^- = df_x^- \quad (12b)$$

$$v_t^+ = \mu \nabla^2 v^+ - (v^+ - df_y^+)(df_y^+)^2, \quad v_0^+ = df_y^+ \quad (12c)$$

$$v_t^- = \mu \nabla^2 v^- - (v^- - df_y^-)(df_y^-)^2, \quad v_0^- = df_y^- \quad (12d)$$

These four equations in (12) are decoupled and, therefore, can be solved as separate scalar partial differential equations in u^+ , u^- , v^+ and v^- . Compared with (3), (10) uses $\mathbf{df}^2$ instead of $|\nabla f|^2$, ensuring that u^+ , u^- , v^+ , and v^- are decoupled from each other. As the snake's orientation has yet to be determined, all the four directions have to be assessed. The DDGVF field of Fig. 1(a) is shown in Fig. 3.

C. Snake Deformation

The external forces of snakes can be classified as static or dynamic forces [14]. Static forces are computed from the image data and do not change as the snake deforms. Dynamic forces are associated with the snake and, therefore, change as the snake deforms. The traditional external forces and GVF are both static external forces. An example of dynamic external force is the pressure inside a balloon [3], which causes the snake to inflate or deflate by a constant force along the normal direction of the contour.

The DDGVF field $\mathbf{v}$ is derived from the image as well as GVF field; however, it cannot be directly applied to the snake as a static external force. For each snaxel in deformation, the external force it is subjected to is dependent on the snaxel's

Fig. 3. DDGVF field in the (a) x , (b) $-x$, (c) y , and (d) $-y$ directions for positive step edges.

Fig. 4. Difference between (a) DDGVF snake and (b) DGVF snake. The arrows indicate the directions of edge in which snakes seek for boundary. In (b), the reference point is marked by “R.”

location in the image and the shape of the snake [Fig. 4(a)]. Hence, the DDGVF field is essentially a dynamic external force.

Let θ be the contour's normal direction at a certain snaxel, then $\cos(\theta)$ is the normal vector's component in the x direction, and $\sin(\theta)$ is the normal vector's component in the y direction. If $\cos(\theta)$ is more/less than zero, u^+/u^- should be used as the horizontal external force F_x at that snaxel. Similarly, If $\sin(\theta)$ is more/less than zero, v^+/v^- should be used as the vertical external force F_y at that snaxel

$$F_x = u^+ * \max\{\cos(\theta), 0\} - u^- * \min\{\cos(\theta), 0\} \quad (13a)$$

$$F_y = v^+ * \max\{\sin(\theta), 0\} - v^- * \min\{\sin(\theta), 0\}. \quad (13b)$$

Hence, the snake is deformed as in (2) under the external force $F_{\text{ext}} = [F_x, F_y]$.

IV. COMPARISON WITH DGVF

In [18], Tang *et al.* proposed a DGVF for snakes, which uses directional gradient to help the snake converge at the correct surface. The edge map function in DGVF is computed by $D_n(I) = \nabla I \cdot \mathbf{n}$, where ∇I is the gradient and $\mathbf{n}$ is the direction of the edge specified by the user. More specifically, $\mathbf{n}$ is the radial direction of each pixel with reference to a point within the object boundary [Fig. 4(b)]. This “radial-search based” strategy has a hidden assumption that the object boundary is a single-valued function in polar coordinates. For some objects of complex shape, the user may not be able to find such a reference point to satisfy the assumption. An example of the edge maps in the DGVF method is shown in Fig. 5.

Fig. 5. Edge maps of DGVF obtained from Fig. 1(a) for (a) positive boundary and (b) negative boundary.

The major difference between DDGVF and DGVF is that DDGVF is a dynamic external force while DGVF is a static external force. As shown in Fig. 4, the edge direction in which DGVF snake seeks for boundary is fixed without considering the shape of the deforming snake while this is not the case for DDGVF snake. The advantage of DDGVF over DGVF is that it makes use of the directional gradient information dynamically in the snake deformation and, thus, achieves better boundary detection results for objects of complex shape. On the other hand, DGVF can have the same good results as DDGVF for objects of simple shape while requires less computational time.

V. PERFORMANCE OF THE METHOD

In this section, the performance of the GVF snake, the DGVF snake and the DDGVF snake are compared. The snakes are dynamically reparameterized during deformation and the distances between neighboring snaxels are maintained within 0.5–1.5 pixels. For each test image, the same initial contour and parameter values are employed for the two snakes. All the edge maps used in snake are normalized to the range [0, 1]. The regularization parameter μ is set to 0.2, and the standard deviation of Gaussian function σ is set to 1.

A. Synthetic Images

In computation of the GVF and DDGVF fields, the number of iteration required to solve the partial differential equations [(3) and (10)] for an image of $m \times n$ pixels is $\sqrt{m \times n}$. During snake deformation, the parameters for snake shape regularization are set as follows: $\alpha = 1$, $\beta = 0$ and $\gamma = 0.6$.

Fig. 6. Performance of GVF, DGVF, and DDGVF snakes on step edge image. The circles of dashed line are initial snake positions and the contours of solid line are final contours of the snakes. Three initial circles of different sizes are used as depicted in the three rows. First column: Results of boundary detection using the GVF snake. Second column: Results of the DDGVF positive boundary-searching snake. Third column: Results of the DDGVF negative boundary-searching snake. Fourth column: Results of the DGVF positive boundary-searching snake. Fifth column: Results of the DGVF negative boundary-searching snake.

1) *Step Edge Images*: The original image is a binary image of an irregular white loop in a black background [Fig. 1(a)]. It is noted that in the edge map of GVF [Fig. 1(b)], the inner boundary and the outer boundary of the loop are both of high intensity because of the magnitude operator. Therefore, these two boundaries are indistinguishable in the GVF edge map and the resultant GVF field.

The effect of initial position of snakes on the performance of the GVF and DDGVF fields in Fig. 1(a) is illustrated in Fig. 6. When the initial contour is not far away from the positive and negative boundaries, it is found that the GVF snake is confused at those regions where the width of the loop is narrow. For two boundaries both of high gradient, the snake is attracted to the boundary which is nearer to the initial boundary [Fig. 6(f)]. When the initial contour is far away from the desired boundaries, the GVF snake is able to converge to the nearer boundary. However at the regions where the two boundaries are very close, the snake is also affected by the GVF field which pulls it to the farther boundary. As a result, the snake stays in the middle of the two boundaries [Fig. 6(a) and (k)]. On the other hand, the DDGVF snake is able to detect definitely the positive boundary [Fig. 6(b), (g), and (l)] or negative boundary [Fig. 6(c), (h), and (m)] independent of the initial contour.

One major advantage of GVF over the traditional potential forces is that it has a much larger capture range. From Fig. 6, we find that the DDGVF possesses the same large capture range as GVF.

As for the DGVF method, the object boundary in this case is regular and the reference center can be easily set as the center of the image. In Fig. 5, the positive and negative boundaries are discerned completely. From the corresponding edge maps, the DGVF snake as well as the DDGVF snake detects the positive and negative boundaries correctly (Fig. 6). However, It does not work for the U-shape object in Fig. 7(a). Because of the concavity in the object boundary, the positive boundary found by the radial search from the reference point is incomplete in the edge map [Fig. 7(b)]. Consequently, the DGVF snake is not able to detect the full object boundary but only the fan-shaped contour in Fig. 7(c). The contour detected by the DDGVF snake is shown in Fig. 7(d).

2) *Line-Drawing Images*: In line-drawing images, the positive and negative boundaries are merged into a single line, and, thus, it is unable and unnecessary to distinguish them. If the image is a line-drawing (black on white), the edge map of GVF can be computed with (4). The GVF converges at the middle of the line-drawing. In this case, since DDGVF uses the same edge

Fig. 7. Performance of DGVF and DDGVF snakes on 176×176 -pixel step edge image. (a) Original step edge image with the initial snake position (circle of dashed line) and the reference point (cross) indicated. (b) Edge map of DGVF. (c) Results of boundary detection using the positive boundary-searching DGVF snake. (d) Results of boundary detection using the positive boundary-searching DDGVF snake.

Fig. 8. Performance of GVF and DDGVF snakes on 176×176 -pixel line-drawing image. (a) Original image of line-drawing with the initial snake position indicated (circles of dashed line). (b) Results of boundary detection using the GVF snake. (c) Results of boundary detection using the line-searching DDGVF snake.

map as GVF [9], the DDGVF snake achieves similarly good result as GVF.

Another major advantage of GVF field is that it is able to move snakes into boundary cavities. This capability is demonstrated in [14] by an image of a U-shaped object [Fig. 8(b)]. In Fig. 8(c), the DDGVF snake also moves downward into the cavity and detect the boundary of the U-shaped object precisely. Thus the DDGVF demonstrates the same ability of converging the snake to the boundary concavity as GVF.

When applied to a point-drawing image [Fig. 9(a)], the DDGVF is also able to converge to a boundary confined by a group of separated points.

B. Natural Images

1) *Photographic Images*: Experiments are performed on images to demonstrate the robustness of DDGVF over the traditional GVF and DGVF methods. Three images: “peppers,” “APC (armored personnel carrier),” and “Garbo” are used. Since the region of interest is relatively small in the images, the GVF, DGVF, and DDGVF fields are computed using $0.5 * \sqrt{m \times n}$ iterations for an image of $m \times n$ pixels. The parameters for snake shape regularization are set as follows:

Fig. 9. Performance of GVF and DDGVF snakes on 176×176 -pixel line-drawing image. (a) Original image of line-drawing with the initial snake position indicated (circles of dashed line). (b) Results of boundary detection using the GVF snake. (c) Results of boundary detection using the line-searching DDGVF snake.

$\alpha = 1$, $\beta = 0$ and $\gamma = 0.6$. The reference point in DGVF edge map is set at the center of the initial contour.

For the first image, our goal is to segment the pepper which lies in the middle. In Fig. 10(b), the bottom-left part of the DGVF snake is attracted by the boundary of the pepper on the left. By contrast, the DGVF and DDGVF snakes prevent the disturbance easily because the desired boundary can be distinguished as a negative boundary. In Fig. 10(c), the DGVF snake fails at the top of the boundary where the stem of the pepper forms a sharp convex. The desired boundary in the second image is the outline of the APC including its shadow. The GVF snake shown in Fig. 10(f) achieves almost the same good result as the DDGVF snake except the indentation at the wheels. In Fig. 10(g), the DGVF snake is unable to include the shadow on the left. The shadow has a vertical line which is nearly on the same line as the reference point, so the DGVF edge map is not able to recognize the shadow’s edge by “radial-search.” For the “Garbo” image, the face contour is to be detected. The GVF snake is largely distracted by the strong edges around the eyes and lips [Fig. 10(j)]. The performance of DGVF snake is not satisfactory in the eye region as can be observed in Fig. 10(k).

In comparison to the above results, the proposed DDGVF field is actually more effective in object/background separation.

2) *Ultrasound Images*: The GVF, DGVF, and DDGVF are also applied to ultrasound images to test their sensitivity to noise. The images are echocardiographic images (short-axis view) of the left ventricle of a human heart. The desired contour

Fig. 10. Performance of GVF, DGVF and DDGVF snakes on photographic images. (a) Image of “peppers” (256×256 pixel). (e) Image of “APC” (192×192 pixel). (i) Image of “Garbo” (128×128 pixel). First column: Original images with the initial snake position indicated (circles of dashed line). Second column: Results of boundary detection using the GVF snake. Third column: Results of boundary detection using the DGVF snake. Fourth column: Results of boundary detection using the DDGVF snake.

is the endocardial boundary of left ventricle. Ultrasound image segmentation has been proven to be intractable to the classic techniques, due to the inherent noisy nature.

In echocardiographic images, the interior of the left ventricle appears darker than the myocardium around, thus the endocardial boundary is roughly a positive boundary. The GVF, DGVF, and DDGVF fields are computed using $0.5 * \sqrt{m \times n}$ iterations for an image of $m \times n$ pixels. Because of the presence of noise, larger α and β ($\alpha = 2$, $\beta = 1$ and $\gamma = 0.6$) are used to confine and regularize the shape of snake.

The performance of GVF, DGVF, and DDGVF snakes when applied to the ultrasound images is shown in Fig. 11. As shown in Fig. 11(b), (f), and (j), the GVF snake fails to detect the real boundaries, at the regions where the potential force propagating from the desired boundary is smaller than that of local noise. Being attracted by not only the positive edges, the GVF snake tends to move to the exterior of the endocardium. The DGVF snake, being able to discern positive boundary from negative

boundary, works better than the GVF snake. However, due to the deficiency of edge map mentioned above, the DGVF snake is not able to reach sharp convex in the contour, e.g., the left corner in Fig. 11(c) and the top-right corner in Fig. 11(g).

In comparison, the DDGVF snake is only attracted to the positive boundaries and is capable of distinguishing the desired edges from the false edges. Thus the proposed DDGVF snake model is superior to the GVF and DGVF snake models for the segmentation of ultrasound images.

VI. CONCLUSION

A new type of dynamic external force for snakes called DDGVF is proposed. The method generates the external force field in the x and y directions separately to preserve the directional gradient information. Since the DDGVF field is utilized dynamically according to the orientation of snake in deformation, the DDGVF snake is attracted to the positive or

Fig. 11. Performance of GVF, DGVF and DDGVF snakes on 220×220 -pixel ultrasound images. First column: Original echocardiographic images with the initial snake position indicated (circles of dashed line). Second column: Results of boundary detection using the GVF snake. Third column: Results of boundary detection using the DGVF snake. Fourth column: Results of boundary detection using the DDGVF snake.

negative step edges exclusively, regardless of the proximity of the two types of edges. The DDGVF snake also demonstrates good convergence and large capture range. This algorithm is particularly useful for snake-based segmentation of object with complex boundary.

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