Boundary detection in echocardiographic images by directional gradient vector flow

Krishnan, Shankar M.; Cheng, Jierong; Foo, Say Wei

2004

Cheng, J., Foo, S. W., & Shankar, M. K. (2004). Boundary detection in echocardiographic images by directional gradient vector flow. IEEE International Workshop on BioMedical Circuits & Systems 2004: Singapore: IEEE.

<https://hdl.handle.net/10356/90848>

<https://doi.org/10.1109/BIOCAS.2004.1454122>

IEEE International Workshop on BioMedical Circuits & Systems © 2004 IEEE. Personal use of this material is permitted. However, permission to reprint/republish this material for advertising or promotional purposes or for creating new collective works for resale or redistribution to servers or lists, or to reuse any copyrighted component of this work in other works must be obtained from the IEEE. This material is presented to ensure timely dissemination of scholarly and technical work. Copyright and all rights therein are retained by authors or by other copyright holders. All persons copying this information are expected to adhere to the terms and constraints invoked by each author's copyright. In most cases, these works may not be reposted without the explicit permission of the copyright holder.
<http://www.ieee.org/portal/site>.

BOUNDARY DETECTION IN ECHOCARDIOGRAPHIC IMAGES BY DIRECTIONAL GRADIENT VECTOR FLOW

Jierong Cheng, Say Wei Foo and Shankar M. Krishnan

School of EEE, Nanyang Technological University, Singapore

ABSTRACT

Snakes, or *active contour models*, have been widely used in image segmentation. In this paper, a new type of dynamic external force for snakes named *directional gradient vector flow* (DGVF) is proposed for the detection of left ventricular boundary from echocardiographic images. The new method is able to discern between positive and negative step edges by incorporating directional gradient information. It makes use of the gradients in both x and y directions and deals with the external force field for the two directions separately. The DGVF field is utilized dynamically in snake deformation, according to the orientation of snake in each iteration. Experimental results demonstrate that the DGVF snake performs better boundary detection than gradient vector flow (GVF) snake in noisy echocardiographic images.

1. INTRODUCTION

Snakes was first proposed by Kass *et al.* [1]. Since its publication, deformable models have become one of the most active and successful research areas in image segmentation [2]. Snakes have been widely applied in boundary detection, shape modeling, and motion tracking etc. Various improvements of snakes have been proposed for applications in medical images, such as multiple active contour model [3], early vision-based snake model [4], cell-based dual snake model [5], and fast GVF (FGVF) [6]. However, very few publications are available on the problem of the direction of gradient.

Most digitalized medical images are gray-level images. The gradient is a valuable information for image processing and analysis. In this paper, a new method named directional gradient vector flow (DGVF) incorporating directional gradient information is proposed. Experimental results show that the method is able to improve the effectiveness of snakes for boundary detection in echocardiographic images. In the next section, a revision of the traditional snake and the gradient vector flow (GVF) snake is given. In Section 3, the DGVF algorithm is presented in detail. The experimental results are given in Section 4 and the conclusion in Section 5.

2. SNAKE AND GVF

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 min-

imize the following energy function:

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

In Eqn. (1), the first two terms comprise the internal energy of the snake. The first-order derivative controls stretching and the second-order derivative controls bending. α and β are the weighing parameters controlling the snake's tension and rigidity respectively. The external energy E_{ext} is derived from the image and set to small values at the features of interest. As object boundaries are usually of high gradient in the image I , a typical example of external energy for step edges is $-|\nabla(G_\sigma(x, y) * I(x, y))|^2$ [1].

The external force F_{ext} is derived from external energy and defined so as to attract the snake to strong edges:

$$F_{ext}(\mathbf{x}) = -\nabla E_{ext}(\mathbf{x}). \quad (2)$$

There are two key drawbacks associated with traditional snakes. Firstly, 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. Secondly, poor convergence may result as the snake has difficulty evolving to concavities or sharp corners.

To solve the problem of limited capture range and poor convergence, Xu and Prince proposed GVF as a new external force for snakes [7]. The external force in Eqn. (2) 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 equation:

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

where $\mathbf{v}_t$ denotes the partial derivative of $\mathbf{v}$ with respect to time 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 large values at the features of interest. A typical choice of f is

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

for step edges.

As the GVF field is calculated as a diffusion of the gradient vectors of an edge map derived from the image, it greatly increases the capture range of the snake and the ability to move into boundary concavities.

In snakes, the role of external force is to attract the deformable contour to the features of interest in an image. However, both traditional snakes and GVF snakes

define their 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 gradients, the snake is unable to distinguish between positive and negative step edges.

3. DIRECTIONAL GVF

In this section, a new approach using directional gradient vector flow (DGVF) is described for snakes 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. In echocardiographic images, the interior of the left ventricle appears darker than the myocardium around, thus the endocardial boundary is roughly a positive boundary.

3.1. Directional edge map

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

$$\mathbf{g}(x, y) = \nabla(G_\sigma(x, y) * I(x, y)) = (g_x(x, y), g_y(x, y)) \quad (5)$$

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

Considering a one-dimensional signal, there are two opposite directions to look through it: x and $-x$. Suppose in the x direction, d_1 is a positive step edge and d_2 is negative. Then 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 obtained will depend on the direction of approach.

Similarly in two-dimensional case, detection of a positive (or negative) boundary is dependent on the direction approached, which associates with the deformable contour's normal direction at each snaxel (snake element). As the location of snake is unknown before initialization, image gradients from all directions are considered. For positive boundary:

$$f_x^+(x, y) = \max\{g_x(x, y), 0\} \quad (6a)$$

$$f_x^-(x, y) = -\min\{g_x(x, y), 0\} \quad (6b)$$

$$f_y^+(x, y) = \max\{g_y(x, y), 0\} \quad (6c)$$

$$f_y^-(x, y) = -\min\{g_y(x, y), 0\} \quad (6d)$$

and for negative boundary:

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

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

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

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

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 the directional edge map $\mathbf{f}(x, y) = [f_x^+(x, y), f_x^-(x, y), f_y^+(x, y), f_y^-(x, y)]$ is obtained.

3.2. Directional GVF field

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

$$\mathbf{v}_t = \mu \nabla^2 \mathbf{v} - (\mathbf{v} - \mathbf{d}\mathbf{f}) \mathbf{d}\mathbf{f}^2, \quad \mathbf{v}_0 = \mathbf{d}\mathbf{f} \quad (8)$$

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

$$df_x^+ = \frac{\partial}{\partial x} f_x^+ \quad (9a)$$

$$df_x^- = \frac{\partial}{\partial x} f_x^- \quad (9b)$$

$$df_y^+ = \frac{\partial}{\partial y} f_y^+ \quad (9c)$$

$$df_y^- = \frac{\partial}{\partial y} f_y^- \quad (9d)$$

or write Eqn. (8) separately

$$u_t^+ = \mu \nabla^2 u^+ - (u^+ - df_x^+)(df_x^+)^2, \quad u_0^+ = df_x^+ \quad (10a)$$

$$u_t^- = \mu \nabla^2 u^- - (u^- - df_x^-)(df_x^-)^2, \quad u_0^- = df_x^- \quad (10b)$$

$$v_t^+ = \mu \nabla^2 v^+ - (v^+ - df_y^+)(df_y^+)^2, \quad v_0^+ = df_y^+ \quad (10c)$$

$$v_t^- = \mu \nabla^2 v^- - (v^- - df_y^-)(df_y^-)^2, \quad v_0^- = df_y^- \quad (10d)$$

The four equations in Eqn. (10) are decoupled, and therefore can be solved as separate scalar partial differential equations in u^+ , u^- , v^+ and v^- . Compared with Eqn. (3), Eqn. (8) uses $\mathbf{d}\mathbf{f}^2$ instead of $|\nabla f|^2$, ensuring that u^+ , u^- , v^+ and v^- are decoupled from one another. The four directions have to be assessed as the snake's orientation cannot be determined at this stage.

3.3. Snake deformation

The external force of snakes can be classified as static or dynamic forces [7]. 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. For the traditional snake, external forces and GVF are both static external forces. The DGVF field $\mathbf{v}$ is derived from the

image as well as GVF field, but it cannot be directly applied to the snake as a static external force. For each snaxel in deformation, the external force which it is subject to depends on its location in the snake and the shape of the snake. Hence the DGVF 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 the horizontal external force F_x at that snaxel. Similarly, If $\sin(\theta)$ is more/less than zero, v^+/v^- should be the vertical external force F_y at that snaxel. Hence the snake is deformed under the external force $F_{ext} = [F_x, F_y]$:

$$F_x = u^+ * \max\{\cos(\theta), 0\} - u^- * \min\{\cos(\theta), 0\} \quad (11a)$$

$$F_y = v^+ * \max\{\sin(\theta), 0\} - v^- * \min\{\sin(\theta), 0\} \quad (11b)$$

4. EXPERIMENTAL RESULTS

In this section, the performance of the GVF snake and the DGVF snake are compared. All the edge maps used in snake are normalized to the range $[0, 1]$. The snakes are dynamically reparameterized during deformation and the distances between neighboring snaxels are maintained within 0.5-1.5 pixels.

The synthetic image is a binary image of an irregular gray loop in a black background (Fig. 1). Snakes, initialized as circles of different radii, deform with the GVF and DGVF fields to detect the boundaries in the original image. 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 (Fig. 2(b)). For two boundaries both of high gradient, the snake is attracted to the boundary which is nearer to the initial boundary. When the initial contour is far away from the desired boundaries, the GVF snake converges 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. 1(d)). On the other hand, the DGVF snake is able to detect the positive boundary (Fig. 2(c), Fig. 1(e)) or the negative boundary (Fig. 1(c), Fig. 1(f)) without problem and independent of the initial contour.

An illustration of GVF and DGVF snakes applied to real images is shown in Fig. 2. The images are echocardiographic images (short-axis view) of the left ventricle of a human heart, and the endocardial (inner) boundaries are to be detected. Ultrasound image segmentation has been proved to be intractable to the classic techniques, due to the inherent noisy nature. In Fig. 2(b), 2(e) and 2(h), the GVF snake fails to derive the real boundaries, at the regions where the external force propagated from the desired boundary is smaller than that of local noise. In comparison, the

Fig. 1. Boundary detection performance of GVF and DGVF snake on synthetic image. The circles of dashed line are initial snake positions and the contours of solid line are final results of the snakes. (a), (d) result of the GVF snake; (b), (e) results of the DGVF positive boundary-searching snake; (c), (f) results of the DGVF negative boundary-searching snake.

DGVF snake is only attracted to the positive boundaries and thus is better able to distinguish the desired edges from the false edges. It is reasonable to conclude that the proposed DGVF snake model is superior to the GVF snake model for boundary detection in echocardiographic images.

5. CONCLUSION

A new type of dynamic external force for snakes called directional gradient vector flow (DGVF) is proposed. The utilization of directional gradient information helps to discern between positive and negative step edges, and thus the DGVF snake can detect the boundary more precisely despite of the noise and artifacts in ultrasound images. This algorithm is particularly useful for snake-based boundary detection of echocardiographic images.

6. REFERENCES

- [1] M. Kass, A. Witkin, and D. Terzopoulos, "Snakes: active contour models," in *Pro. Int'l Conf. Computer Vision, ICCV'87*, (London), 1987.
- [2] C. Xu, D. L. Pham, and J. L. Prince, "Image segmentation using deformable models," in *Handbook of Medical Imaging: Volume 2. Medical Image Processing and Analysis* (M. Sonka and J. M. Fitzpatrick, eds.), ch. 3, pp. 129–174, SPIE Press, 2000.
- [3] V. Chalana, D. T. Linker, D. R. Haynor, and Y. Kim, "A multiple active contour model for cardiac boundary detection on echocardiographic

Fig. 2. Boundary detection performance of GVF and DGVF snake on echocardiographic images. The circles of dashed line are initial snake position and the contours of solid line are final result of the snakes. (a), (d), (g) Original echocardiographic images with the initial snake position indicated; (b), (e), (h) results of the GVF snake; (c), (f), (i) results of the DGVF snake.

sequences,” *IEEE Trans. Med. Imag.*, vol. 15, pp. 290–298, 1996.

- [4] C. Chen, H. Lu, and Y. Huang, “An early vision-based snake model for ultrasound image segmentation,” *Ultrasound in Med. & Biol.*, vol. 26, pp. 273–285, 2000.
- [5] C. Chen, H. Lu, and Y. Huang, “Cell-based dual snake model: a new approach to extracting highly winding boundaries in the ultrasound images,” *Ultrasound in Med. & Biol.*, vol. 28, pp. 1061–1073, 2002.
- [6] M. Wei, Y. Zhou, and M. Wan, “A fast snake model based on non-linear diffusion for medical image segmentation,” *Computerized Medical Imaging and Graphics*, vol. 28, pp. 109–117, 2004.
- [7] C. Xu and J. L. Prince, “Snakes, shapes, and gradient vector flow,” *IEEE Trans. Image Processing*, vol. 7, pp. 359–369, 1998.