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Development of an accelerated GVF semi-automatic contouring algorithm for radiotherapy treatment planning

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ABSTRACT

Fast contouring is important in image-guided radiation therapy (IGRT) and adaptive radiation therapy (ART) where large computed tomography (CT) volumes have to be segmented. In this study, a modified active contour (also called snake) segmentation method based on a faster gradient-vector-flow (GVF) calculation algorithm is proposed. The accelerated method was tested on multiple organs, including lung, right ventricle, kidney and prostate. Compared to the original algorithm, the improved one reduced GVF calculation times to one-half or less without compromising contour accuracy.

1. Introduction

Computed tomography (CT), magnetic resonance imaging (MRI) and other volume imaging modalities are part of modern radiotherapy. By identifying target tissues and avoidance structures, treatments can be tailored to maximize tumor doses while keeping doses to critical structures low, to preferentially kill tumor cells in the target while minimizing damage to normal surrounding structures. Adaptive radiotherapy (ART) involves frequent imaging throughout the course of radiotherapy to take changes of anatomy into account. Image guided radiation therapy (IGRT) requires imaging immediately before treatment so that shifts of internal structures can be compensated for by appropriate shifts of the patient. In all cases, target volumes and critical structures have to be identified. Manual contouring is very tedious, especially in ART and IGRT where repeated imaging is required. In IGRT, a short contouring time is critical to prevent patient motion between imaging and treatment.

To reduce labor and expedite contouring, numerous automatic techniques have been suggested. Ukil and Reinhardt [1] proposed a fully automatic method for three-dimensional (3D) smoothing of the lung boundary using information from the segmented human airway tree. Ragan [2] adopted a commercial prototype deformable model to semi-automatically contour 4D CT image volumes from eight phases in the respiratory cycle. Burnett [3] developed a deformable-template algorithm to segment the spinal canal which was modeled using Fourier descriptors derived from four sets of manually drawn contours. Atlas-based and model-based [4–13] segmentation methods have been widely used for segmenting multiple organs.

A semi-automatic image segmentation algorithm based on active contour (snake) was first proposed by Kass [14] in 1987, and successfully applied in many image processing applications. Since then, several variations have been suggested. The GVF-based snake algorithm was proposed in 1997 by Xu and Prince [15]. Unlike the traditional external forces, GVF forces have a relative large capturing range and can accommodate small concavities, an essential feature in medical applications. However, the relatively long time required to calculate the GVF is a shortcoming of this algorithm. To shorten calculation times, we propose an accelerated variation based on the original algorithm introduced by Xu and Prince. Its performance was tested on clinical examples and compared to the original one.

2. Method and materials

The GVF-based snake model dynamically changes the shape of an initial curve in response to internal (elastic) and external (image and constraint) forces. The internal forces originate from the curve itself, usually from its first and second derivatives as tension and rigidity terms that resist stretching and bending. The GVF, being the external force derived from images, moves the contour toward regions of high gradients.

In a typical snake model, the energy function E to be minimized is defined as

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

where $C(s)$ is the snake curve and $C'(s)$ and $C''(s)$ are the first and second derivatives of $C(s)$ with respect to $s \in [0,1]$. The first two

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items are internal forces from the curve itself. The parameters α controls the tension of the curve, while β controls its rigidity. The external energy function E_{ext} is derived from image features like object boundaries.

The minimization of E in (1) must satisfy the Euler equation

$$\alpha C''(s) - \beta C'''(s) - \nabla E_{ext} = 0 \tag{2}$$

In the GVF snake model [6], the gradient of $E_{ext}(\nabla E_{ext})$ is the gradient vector field,

$$\nabla E_{ext}(x,y) = -V(x,y) = -[u(x,y), v(x,y)] \tag{3}$$

The GVF vector $V(x,y)$ is obtained through the minimization of the energy ε,

$$\varepsilon = \int\int \mu(u_x^2 + u_y^2 + v_x^2 + v_y^2) + |\nabla f|^2 |V - \nabla f|^2 \, dx\, dy \tag{4}$$

where $f(x,y)$ is an edge map. It is defined on the image as

$$f(x,y) = -|\nabla[G_\sigma(x,y) * I(x,y)]|^2 \tag{5}$$

where $G_\sigma(x,y)$ is a two-dimensional (2D) Gaussian function with standard deviation σ and $I(x,y)$ is the image intensity.

For discrete problems like image processing, a numerical implementation for finding $V(x,y)$ has been described by Xu and Prince [6]. Being an iterative process involving the entire 2D image matrix, the search for $V(x,y)$ is quite time consuming, even when performed on a modern high speed computer.

To speed up that search, we have added the acceleration terms $\xi e^{-n/N_0}(u_{i,j}^n - u_{i,j}^{n-1})$ and $\xi e^{-n/N_0}(v_{i,j}^n - v_{i,j}^{n-1})$ to the equations for the GVF vector field components, so that they become

$$\begin{aligned} u_{i,j}^{n+1} &= (1 - b_{i,j}\Delta t)u_{i,j}^n + \gamma(u_{i+1,j}^n + u_{i,j+1}^n + u_{i-1,j}^n + u_{i,j-1}^n - 4u_{i,j}^n) \\ &\quad + c_{i,j}^1 \Delta t + \xi e^{-n/N_0}(u_{i,j}^n - u_{i,j}^{n-1}) \\ v_{i,j}^{n+1} &= (1 - b_{i,j}\Delta t)v_{i,j}^n + \gamma(v_{i+1,j}^n + v_{i,j+1}^n + v_{i-1,j}^n + v_{i,j-1}^n - 4v_{i,j}^n) \\ &\quad + c_{i,j}^2 \Delta t + \xi e^{-n/N_0}(v_{i,j}^n - v_{i,j}^{n-1}) \end{aligned} \tag{6}$$

where $b_{i,j}, c_{i,j}^1, c_{i,j}^2$ and γ are defined and calculated as described in [16]. ξ is a scaling constant, N_0 is the maximum iteration number and Δt is the time step, equal to unity in this case. The acceleration terms are relatively large at the beginning of the search to speed up convergence and, to avoid oscillation, become smaller as the number of iterations increases. The search for the GVF is terminated after a predetermined number of iterations or when the convergence parameter ρ has reached a preset value. The convergence parameter ρ is defined as the largest change between consecutive iterations of the absolute value of any of the gradient vectors $V(x_i, y_j)$, i.e.,

$$\rho = \max_{i,j}\left\{\sqrt{(u_{i,j}^{n+1} - u_{i,j}^n)^2 + (v_{i,j}^{n+1} - v_{i,j}^n)^2}\right\} \tag{7}$$

A large value of ρ indicates that the optimal GVF has not yet been found, whereas a small value of ρ suggests that the search is converging and only marginal improvement can be achieved by additional iterations. In a clinical application, a compromise has to be made between the conflicting requirements of short calculation times and accuracy.

After the GVF vector $V(x,y)$ has been computed using the accelerated algorithm, Eq. (2) can be written in discretized form

$$C_t(s,t) = \alpha C''(s,t) - \beta C'''(s,t) + V \tag{8}$$

It is solved by an iterative method similar to the equation containing the GVF field obtained by the original search algorithm. The search for the optimized contour is terminated when image entropy of the segmented region, defined as

$$H = -\sum_{i=1}^{N} p_i * \log\, p_i \tag{9}$$

changes between consecutive iterations by less than a preset small value. In Eq. (9), N is the number of pixel bins in the search region and p_i is the fraction of pixels contained in the ith bin. We used in our study 256 bins of equal width, covering the range between the smallest and the largest CT numbers encountered in the segmented region. The highest acceptable change in entropy between consecutive iterations was chosen as 10^{-3}. We chose such a small number to assure an optimal fit of the contour. Considering the relatively short times required for computing the contour, potential time savings by accepting a larger entropy would have been insignificant.

To evaluate the performance of the accelerated GVF search algorithm, we compared snakes derived from the accelerated GVF to the "Gold Standard" (GS). The GS is defined as the snake obtained from the original GVF search algorithm after a very large number of iterations (2000). The comparison was done using an overlap factor OF, defined as

$$OF = \frac{A_{Accel} \cap A_{Gold}}{A_{Accel} \cup A_{Gold}} \tag{10}$$

where A_{Accel} is the area enclosed by the contour resulting from the GVF derived from the accelerated algorithm, and A_{Gold} is the area enclosed by the GS. With this definition, $OF = 1$ is indicative of a perfect match between the two contours, whereas $OF = 0$ would indicate absence of any overlap.

3. Results

Fig. 1 shows the effect of the GVF convergence parameter ρ on the quality of segmenting. A value of $\rho = 10^{-2}$ results in a contour that misses in many places the outline of the lung (b). A decrease of ρ to 10^{-3} yields an accurate lung contour (d), whereas a further decrease to 10^{-4} yields an improved GVF (e) but fails to substantially improve the contour (f). An illustration of the rapid convergence of the accelerated algorithm in comparison with the original one is shown in Fig. 2. Starting from an initial hand-drawn contour, the accelerated algorithm achieved a convergence parameter of 10^{-3} after 44 iterations and 1 s computation time (c), yielding a contour that accurately follows the lung outline (d). After performing the same number of iterations, the original algorithm yielded a vector field with convergence parameter 1.62×10^{-3} (a). The contour resulting from that vector field failed to follow the intricate outline of the lung in its 3-o'clock position (b). It took the original algorithm 74 iterations to achieve the convergence of 10^{-3} (e), which resulted in an acceptable contour (f).

To test the clinical performance of the algorithm, lung, right ventricle, kidney and prostate were segmented. In each case, the original and the accelerated algorithms were used to obtain GVFs having equal convergence parameters. The number of iterations and times required for convergences of 10^{-3} and 10^{-4} are summarized in Table 1. The results apply to contours on a single 512×512 pixel slice, calculated with a Pentium 4 desktop computer operating at 3.20 GHz CPU clock speed. For all organs, the acceleration terms used the parameters $\xi = 0.8$, $N_0 = 80$ and $N_0 = 300$ for convergence to 10^{-3} and 10^{-4}, respectively. A quantitative evaluation of the accelerated algorithm is shown in the last two columns of Table 1.

Respiratory gating requires a minimum of two CT scans to determine the extent of tumor motion, one at the end of inspiration and the other at the end of expiration. Because of the large number of images, any automation is welcome. In the example shown in Fig. 3,