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Level-set based vessel segmentation accelerated with periodic monotonic speed function

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ABSTRACT

To accelerate level-set based abdominal aorta segmentation on CTA data, we propose a periodic monotonic speed function, which allows segments of the contour to expand within one period and to shrink in the next period, i.e., coherent propagation. This strategy avoids the contour's local wiggling behavior which often occurs during the propagating when certain points move faster than the neighbors, as the curvature force will move them backwards even though the whole neighborhood will eventually move forwards. Using coherent propagation, these faster points will, instead, stay in their places waiting for their neighbors to catch up. A period ends when all the expanding/shrinking segments can no longer expand/shrink, which means that they have reached the border of the vessel or stopped by the curvature force. Coherent propagation also allows us to implement a modified narrow band level set algorithm that prevents the endless computation in points that have reached the vessel border. As these points' expanding/shrinking trend changes just after several iterations, the computation in the remaining iterations of one period can focus on the actually growing parts. Finally, a new convergence detection method is used to permanently stop updating the local level set function when the 0-level set is stationary in a voxel for several periods. The segmentation stops naturally when all points on the contour are stationary. In our preliminary experiments, significant speedup (about 10 times) was achieved on 3D data with almost no loss of segmentation accuracy.

Keywords: Level-set, image segmentation, monotonic speed function, coherent propagation, narrow band, sparse field

1. INTRODUCTION

Object segmentation is often needed in medical image analysis, e.g., for surgery planning or for quantitative measurements of vessel stenosis. Although there are many segmentation methods in the literature ¹, many of them fail to give satisfactory result when the image has limited resolution or relatively high noise content ². These difficulties can sometimes be overcome by user intervention, but this often results in complicated workflows and long analysis time. The level-set method, invented in the 1980s, has been seen as a promising segmentation tool, due to its ability to automatically handle complicated topological changes of the targeted object, keep the contour smooth on a noisy background and generate segmentation results with sub-voxel accuracy ³. Many studies have shown that the level-set technique improves the segmentation accuracy and reduces the need for user supervision ^{4,5}. Despite the success and robustness achieved in various experimental environments, its application in clinical practice is still rather limited, mainly due to the long computation time. Several methods have been proposed to accelerate the level-set method; for example Sethian et al invented the narrow-band method, in which the computation of the level-set function is limited to a band a few pixels wide instead of the whole image ⁶. Whitaker later extended narrow-band level set to the sparse field level set, where the narrow band is only one pixel wide and the level set function is recalculated with a distance transform in each iteration ⁷. However, in our abdominal aorta segmentation task, these methods did not give satisfactory performance, as it still takes more than 1 minute to segment the aorta from a 256×256×256 volume.

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In our early experiments, we noticed that, when certain points during propagating move faster than their neighbors, the curvature force will move them backwards to keep the contour smooth, even though the whole neighborhood will eventually move forwards. This kind of local wiggling behavior slows down the propagation considerably. In this paper, we propose a modified sparse field level set method, which uses a periodic monotonic speed function, resulting in coherent propagation of the boundary. The speed function avoids local wiggling by letting the local neighborhood of the contour expand together in one period and shrink in the next period. Coherent propagation also allows us to implement a lazy narrow band level set algorithm which prevents the repeated computation in points that have reached the vessel border. As these points' expanding/shrinking trend changes just after several iterations, the computation in the remaining iterations of one period can focus on the actually growing parts. Finally, a new convergence detection method is used to permanently stop updating the local level-set function when the 0-level set is stationary on a voxel for several periods. The segmentation stops naturally when all points on the contour are stationary.

2. METHOD

2.1 Stop local wiggling of the level set function with coherent propagation

In the level-set method, a dynamic implicit function ϕ , a signed distance function, represents the object's contour. By iteratively moving this function according to external and internal forces, the 0-level set can be deformed to the shape of the object of interest. In most level-set based segmentation applications, the curvature force (intrinsic factor) is used to keep the contour smooth, whereas the intensity, gradient and texture of the image (extrinsic factors) are used to attract the contour into the border of object (Equation 1 gives a typical example, $C(x,t)$ is the local curvature, $D(x)$ is an intensity-based external force). Due to noise and numerical errors, the neighbor points on the 0-level set (the contour) will not propagate at the same pace. Very soon they will form a zigzag shape, even if they start from the same line (Fig. 1a–c). The faster points (point 2 and 4 in Fig. 1b) in the neighborhood will be “pushed” back by the curvature force in the next iteration, while the trend of the local segment is to move forward. As this phenomenon is repeated during the level set function's evolution, this local wiggling problem significantly slows down the propagation speed.

$$\frac{\partial \phi}{\partial t} = v_t, \text{ where } v_t = \alpha C(x,t) + (1 - \alpha)D(x) \quad (1)$$

We propose to replace the conventional speed function with a periodic monotonic function to avoid the local wiggling problem, as shown in equation 2.

$$\frac{\partial \phi}{\partial t} = w(v_t) \text{ where } w(v_t) = \begin{cases} v_t & (\text{if } v_t \times \text{trend}(x,t) > 0) \\ 0 & (\text{if } v_t \times \text{trend}(x,t) \leq 0) \end{cases} \quad (3)$$

“trend” represents whether the local contour is expanding or shrinking. Its value can only be 1 or -1; as in level set the function v_t is a scalar. “trend” for each pixel/voxel is initialized at the first time when it is added into the narrow band, using $\text{sign}(v_t)$. Its values need not be the same across the image, but they will change sign at the same time. “trend” will change sign at the end of a period when $w(v_t)$ is 0 (i.e. $v_t \times \text{trend} \leq 0$) for every point on the narrow band.

As shown in Fig. 1d–f, using this periodic monotonic speed function, the faster points (point 2 and 4 in Fig. 1e) will not move back due to slower neighbors (because $v_t \times \text{trend} < 0$), but stay in place and wait for the neighbors to catch up. Then, as the contour becomes flat again (Fig. 1f), v_t at point 2 and 4 will have the same sign as trend, and all points can move forward together. The initialization of the trend is not crucial. Even if one point's trend is opposite to the neighbors' due to noise, the contour can still propagate around the point and merge again after the point, thanks to the level set's ability to automatically handle topology changes. The left-behind noise island will be eliminated in the next period due to the high curvature.

In this way, the expanding parts of the contour keep expanding, and the shrinking parts keep shrinking in a coherent manner, until they reach the boundary of the segmented object. As the force related to extrinsic factors will change sign when the contour has crossed the boundary, these parts of the contour can no longer expand or shrink. At the same time, the curvature force will prevent the contour from growing into corners by changing their sign and never changing back.

Then $w(v_i)$ becomes 0 everywhere on the contour. After *trend* of each point has changed sign, different parts of the contour will change their propagation direction to compensate for the error caused by their crossing the border in the preceding period. As *trend* periodically changes its sign, the contour will converge on the border of the object.

Figure 1, a-c, demonstrate the local wiggling problem: The faster points in the neighborhood will be “pushed” back by the curvature force in the second iteration, while the trend of the local segment is to move forward. d-f: using periodic monotonic speed function avoids local wiggling as the points move monotonically.

2.2 A lazy version of the sparse field level set algorithm

Solving equation 1 for every pixel/voxel in the image is very time-consuming. The sparse field level-set algorithm, proposed by Whitaker, calculates new ϕ only on the pixels/voxels where the 0-level set passes by, and updates their neighbors’ level set function (2–3 pixels/voxels away) via a distance transform. This reduces the computation by one order of magnitude. However, in the conventional implementation, all the points on the one pixel wide narrow band need to be updated during each iteration, even if many parts of the contour have converged on the border of the object. With coherent propagation, in a single period, if the contour reaches the border, $w(v_i)$ of that part of contour will become 0. If no neighbor changes its value, $w(v_i)$ will always return 0 in the remaining iterations in that period. We can simply put these points to “sleep” and stop updating the level set function here. As these points may be just in a temporal “equilibrium” ($w(v_i) = 0$), a wakeup mechanism is implemented to allow all changed points ($w(v_i) \neq 0$) to wake up sleeping points in a 1–2 pixel/voxel wide neighborhood. Moreover, the changed points can only wake up the neighbor points with the same *trend*, as it means that the neighbors are catching up. Otherwise they are following further behind, and $w(v_i)$ remains 0. At the end of a period, all the sleeping points are waked up again. As most points are close to the vessel border, they will be put to sleep after 1–2 iterations.

2.3 Forced convergence

In most sparse field level-set implementations, numerical errors from reinitializing the level-set function (signed distance computation) and from solving the partial differential equation cause the speed v_i to hardly ever converge to 0; instead it keeps jumping around 0 in small steps (mostly less than 1 pixel). When a periodic monotonic speed function is used, the contour will, in most cases, still converge in the same manner. But at certain locations, especially at the sharp corners where v_i is dominated by the curvature force, the contour can jump in larger steps (Fig. 2a). This is caused by the small step jumping of the joint points (the circled area in Fig. 2a) will allow the elastic region between them to change dramatically. One solution is to switch to a conventional speed function after several periods. However, in our implementation we have adopted a more efficient method to force the elastic region to converge by stopping the update of the level set function permanently on those points where the 0-level set have stayed for several periods. A wiggling counter was used to track how many periods the 0-level set stays on each pixel/voxel. At the end of each period, this counter is increased by 1 for each point on the one pixel wide narrow band (0-level set). In Fig. 2a, after one period the counter of pixels on the 0-level set (all blue pixels including those overlapped with green pixels beneath the joint points)

is increased to 1; after 2 periods, the counter of the green pixels is increased by 1. For the overlapped segments beneath the two jointing points, because the extrinsic forces (gradient or intensity), the change of their level set value is usually small (jumping between -0.5 and 0.5). The 0-level set stayed on those points for 2 periods, and therefore their counters become 2. When the counter for one active point goes above a given threshold (typically 10 in our experiments), it is set to permanent sleep. The permanent value at that point is then calculated as the mean of the current value and the value at the end of last period. This will in turn cause their active neighbors, if there are any, jump in smaller steps. As can be expected, the joint area in Fig. 2a will become stationary first, and the jumping of the elastic region is gradually stopped from both ends (red curve in Fig. 2b).

Figure 2. a: Using a periodic monotonic speed function causes the contour to jump between the blue and green lines. b: The red curve represents the final result when a wiggling counter is used, the yellow line is the result from conventional level-set segmentation

Figure 3. Column a,b: Synthetic images (SNR=10 dB), Column c: CT image. In all cases, seed region upper row, and segmentation results lower row.

3. RESULTS

Both 2D and 3D versions of the proposed method were implemented as a single-thread application on a Mac Pro with a 2.93GHz Intel Xeon CPU. The $D(x)$ term in the speed function v_i (Equation 1) is set to a threshold-based function: $D(x) = \varepsilon - (I(x) - T)$, where $I(x)$ is the intensity of input image, T is the center of threshold window and ε is the width of the window, as described in ⁸. 2D synthetic and clinical images were tested (Fig. 3 shows a few examples). In general, 5–15 times speedup was achieved compared with the conventional sparse field level set method. Typical computation time for a 512×512 image was 0.1–0.2 s. With the 3D version, 12 cases of abdominal aorta CTA data were tested. A single seed region (as in Fig. 4a) was provided for each case. About 10–20 times speedup was achieved. Typical computation time for a 256×256×256 volume was 5–12 s. The difference between our method and the conventional method was measured by comparing the distance (given directly by the level set function) of the points on the one voxel wide narrow band. As the conventional method tends to stop growing earlier than the proposed method, only points around the abdominal aorta trunk were counted. In the 12 datasets, the distance between two 0-level sets varied from −1.80 to 1.46 voxel units (a negative distance means that the contour point from proposed method is outside the contour from conventional method), and the mean signed distance was −0.12 with standard deviation 0.11. The mean unsigned distance (absolute value) between two contours was 0.13 (with standard deviation 0.10, however it is not a normal distribution). In total, 35 segmented voxels had a distance to the conventional results of more than 1 voxel unit. Fig. 4c shows a coarse comparison based on subtraction of two binary masks generated by thresholding the final level set outputs.

Figure 4. a: Seed region; b: Segmentation result; c: Difference compared with conventional level-set segmentation. Note that new parts of the splenic artery are now included in the segmentation (but not part of the statistical comparison which only considers the main aortic trunk)

Figure 5. Comparison of actually computed voxels in each iteration (blue: sparse field level set, red: lazy narrow band level set), red spikes indicate the start of periods when all sleeping points wake up. Most points were stopped after several period as the 0-level set became stationary.

4. DISCUSSION

Many methods have been proposed to speed up level-set based image segmentation. Some of them⁹ focus on speeding up the convergence of the level-set function, whereas other methods^{6,7} focus on skipping the unnecessary computation of points further away or not changing⁸. The proposed method achieved significant speed-up by using both strategies.

Firstly, the coherent propagation makes the 0-level set approach the border of the object faster. Not only can the faster points avoid moving backwards to wait for their slower neighbors, but also the step length for all points is increased in each iteration by allowing the Δt to be somewhat bigger. In all level set algorithms, to make sure the stability of the level set function, it is required that $\Delta t \times v_t$ is less than one pixel/voxel unit for all the points on the 0-level set (otherwise the connectivity of the 0-level set will break). As Δt is unified for all points, it requires the algorithm to choose the maximum v_t among all the points in the narrow band in each iteration, and limits the Δt to be less than $1/|v_{t-max}|$. Often the points moving backward will have the highest velocity; Δt is therefore limited by these points. By setting v_t to zero in these points, the absolute value, $|v_{t-max}|$ can be smaller, which makes the remaining points require fewer iterations to move one pixel unit. Lthen et al.⁹ have proposed a momentum based optimization method for level set segmentation to speed up the convergence, which determines the current contour points' speed by combining the in/extrinsic forces and the speed in last iteration: $((1-\omega)v_t + \omega v_{t-\Delta t})$, where an ω of 0~0.4 is recommended by the author). This has a similar effect as our method in keeping the points moving in one direction. However, it is difficult to choose ω , as if ω is too big, the 0-level set on a noisy background will jump around the border and never converge; on the other hand, if ω is too small, the points will still move backwards. Using a periodic monotonic speed function, it is easier to ensure convergence, at least within one period. Just like the momentum-accelerated level set, the periodic monotonic speed function also tends to pass over local minima, such as stenoses in a vessel branch⁹, as shown in Fig. 5.

Secondly, unnecessary computation is skipped by implementing a modified sparse field level set method. Unlike the conventional narrow band or sparse field level set methods, implementing the lazy narrow band level set algorithm with a new convergence detection method allows us to avoid not only computing points that are far away from the 0-level set, but also repeating useless computation on the converged segments of the contour, and instead focus on the actively changing parts. Fig. 4d gives an overview of how many points are computed in each iteration, compared with a sparse field level set algorithm running on the same data with same parameter settings. In our experience, the segmentation accuracy is not sensitive to the threshold set on the wiggling counter. In our experiments this threshold was set to 10 in 2D cases and 5 in 3D cases.

Recently, Roberts et al proposed a GPU version of the sparse field algorithm, in which they also proposed to stop computing the locally converged points by analyzing the temporal equilibrium of the local gradient³. However, in our opinion, it is still difficult to detect such an equilibrium when the 0-level is wiggling around the object's border, unless high accuracy is used in the partial differential equation solver and distance transform. Moreover their method, in special cases, will prematurely stop the local propagating at certain local optima. In our method, stopping the propagating prematurely is avoided since, after the first period, the contour has already shrunk/expanded to a location near the global optimum.

The proposed level set method with coherent propagation achieved by a periodically monotonic speed function may, at a first glance, seem similar to the monotonic level set method – fast marching¹⁰. However, unlike fast marching, the curvature force in coherent propagation can still be used to avoid leaking problems (Fig. 3c); the propagating contour can expand and shrink at the same time, and the topological changes of the contour are still automatically handled (Fig. 3a, b). The potential to perform the computation in parallel on multi-core CPU or GPU should also be considered when comparing with the fast marching method.

5. CONCLUSION

In conclusion, the contribution of this paper includes: (1) introducing a periodic monotonic speed function into the level set function to speed up convergence, (2) implementing a lazy narrow band level set algorithm and (3) using a new convergence detection method. In our preliminary experiments, significant speedup (about 10 times) was achieved on 3D data with almost no loss of segmentation accuracy

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