Improved Interactive Medical Image Segmentation using Enhanced Intelligent Scissors (EIS)

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***Abstract*— A novel interactive approach called Enhanced Intelligent Scissors (EIS) is presented for segmenting regions of interest in medical images. The proposed interactive medical image segmentation algorithm addresses the issues associated with segmenting medical images and allows for fast, robust, and flexible segmentation without requiring accurate manual tracing. A robust complex wavelet phase-based representation is used as an external local cost to address issues associated with contrast non-uniformities and noise typically found in medical images. The boundary extraction problem is formulated as a Hidden Markov Model (HMM) and the novel approach to the second-order Viterbi algorithm with state pruning is used to find the optimal boundary in a robust and efficient manner based on the extracted external and internal local costs, thus handling much inexact user boundary definitions than existing methods. Experimental results using MR and CT images show that the proposed algorithm achieves accurate segmentation in medical images without the need for accurate boundary definition as per existing Intelligent Scissors methods. Furthermore, usability testing indicate that the proposed algorithm requires significantly less user interaction than Intelligent Scissors.**

I. INTRODUCTION

An important task in medical image processing is segmentation, where regions of interest such as organs and bone structures are partitioned from the rest of the image content. Medical image segmentation has numerous important applications in clinical analysis, such as tumor detection, tissue classification [1], and growth analysis [2]. Manual medical image segmentation is very laborious, time-consuming, and inaccurate due to the need for manual tracing. Therefore, computer-assisted methods for segmenting regions of interest in medical images are much desired.

Recently, semi-automatic segmentation algorithms have been proposed to overcome some of the issues associated with automatic segmentation [3], [4]. These algorithms allow for user interaction during the segmentation process, thus taking advantage of user knowledge to guide the boundary. Of particular interest are those based on Intelligent Scissors (IS) [6], [7], first introduced by Mortenson et al. [5]. In these methods, the user selects an initial starting point on the boundary and, as the mouse moves along the boundary, the optimal boundary path between the starting point and the current point is shown. There are two main advantages to this approach to segmentation. First, the segmentation is accomplished in real-time as opposed to the iterative approach taken by automatic methods, thus allowing for rapid image segmentation. Second, the boundary accuracy of the segmentation using such methods is generally higher than automatic methods since user knowledge is used throughout the process [5]. However, there are several drawbacks to existing Intelligent Scissor-based methods when used by clinicians for the purpose of medical image segmentation. First, like current automatic segmentation methods, the boundary definition for existing IS methods is refined based on image gradients, making it highly sensitive to contrast non-uniformities typically found in medical images (e.g., static field and RF non-homogeneities in MRI [8], [9]). Second, existing IS methods require the clinician to perform relatively accurate manual tracing along the region boundary, which can be time-consuming and laborious, particularly for complex regions of interest. Therefore, a method that addresses these key issues is desired for the purpose of medical image segmentation.

The main contribution of this paper is an Enhanced Intelligent Scissors (EIS) algorithm designed for rapid medical image segmentation. The proposed method is highly robust to contrast non-uniformities and noise, which are key problems faced in segmenting regions of interest in medical images. Furthermore, the proposed EIS algorithm does not require the user to perform accurate tracing along the region boundary to work properly. This allows for faster user interaction compared to existing IS methods. The proposed method is described in Section II, and experimental results are presented in Section III.

II. PROPOSED METHOD

The proposed EIS algorithm takes a fast interactive approach to the problem of medical image segmentation, where a boundary is formed around the region of interest based on a sequence of user-selected points. The proposed algorithm can be described as follows. First, a phase-based representation of the image is extracted as the external local cost using a robust iterative complex wavelet phase moment estimation scheme. Second, the boundary extraction problem between two user-selected points is treated as an active contour problem and formulated as a HMM. Third, a novel approach of solving the formulated HMM using the second-order Viterbi algorithm is performed by reformulating the second-order problem with first-order Markovian assumptions and solving it based on the internal and external local costs. Furthermore, a novel adaptive state pruning scheme is performed based on the extracted external local costs to significantly reduce the computational complexity of the proposed EIS algorithm.

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A. User Interaction

In the conventional IS approach, the user starts at an initial point near the boundary of the region of interest and moves the mouse cursor closely along the boundary. As the mouse cursor comes close to a boundary edge, a "live-wire" boundary snaps to the edge [5]. Therefore, as the mouse cursor moves around the region of interest, the live-wire wraps around the region to form a segmentation boundary. In the proposed EIS approach, the user first selects an initial point near the boundary of the region, as with the conventional IS approach. However, rather than tracing the mouse cursor closely along the boundary, the user selects a sequence of discrete points around the boundary. As the user selects points around the boundary, the user-selected points snap to the region of interest and a boundary is formed around the region of interest between these points. Therefore, as points are selected, a segmentation boundary is formed. The points selected by the user in EIS can be sparsely spaced around the region boundary and does not need to be placed in close proximity to the region boundary. The main advantage of using the proposed approach of user interaction over the conventional IS approach is that the user does not need to trace around the boundary carefully. The user can simply click around the region boundary in an imprecise manner and the EIS algorithm will automatically create a boundary around the region of interest accordingly. This allows for a much faster level of user interaction while still providing accurate region boundaries based on user knowledge.

B. External Local Cost Extraction

The first step of EIS is to extract a set of external local costs for driving the boundary extraction process. In current Intelligent Scissors methods, the external local costs used are based on the intensity gradients of the image. While these external local costs are acceptable for general image processing applications such as simple image composition [5], they are not well suited to handle the issues associated with medical images such as poor contrast resolution, contrast non-uniformities, and additive or multiplicative noise. In the proposed EIS algorithm, a more suitable external local cost is utilized based on a robust complex wavelet phase-based representation [10]. The phase-based external local cost can be extracted as follows. Given the initial image I_0, an initial estimate of the local phase coherence of the image ρ_0 is extracted. During each new iteration k, the maximum phase coherence moment σ_k is extracted based on the previous local phase coherence estimate ρ_{k-1}. Using σ_k, a revised estimate of the image I_k is determined based on the moment-adaptive bilateral estimation approach [11]. Finally, the re-estimated image I_k is used to re-estimate the local phase coherence ρ_{k+1} to be used by the next iteration of the estimation process. This is performed over n iterations to obtain the final phase-based external local cost l_{ext} as defined by:

$$l_{ext} = \sigma_n \tag{1}$$

where σ_n is the estimated maximum phase coherence moment at the end of n iterations. Based on testing, it was observed that convergence typically occurs at $n = 3$. There are several important benefits in using the proposed phase-based representation as the external local cost. First, it is invariant to contrast non-uniformities typically encountered in medical images (e.g., static field and RF non-homogeneities) since only phase information is used. Second, it is highly robust to signal noise, which is typically found in medical images.

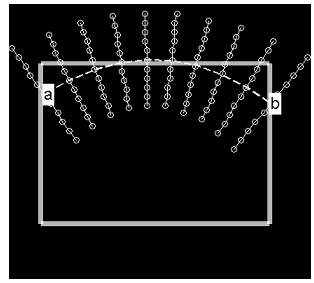

Fig. 1. Trellis for an example boundary between two points a and b. In this example, 10 normals are found along the constructed curve. Each normal is then represented by 11 nodes.

C. Hidden Markov Model of Boundary Extraction Problem

The second step of EIS is to formulate the boundary extraction problem based on the inexact points along the region boundary that the user selects in the user interface. Suppose the user selects two points a and b along the boundary of the region of interest with the coordinates (x_a, y_a) and (x_b, y_b) respectively. In EIS, the boundary extraction problem between two points is formulated using a Hidden Markov Model (HMM). The trellis of the HMM is constructed as follows. First, a curve between points a and b is created and q normals are found along the curve. Each of the q normals is then represented by p nodes, resulting in a total of pq nodes. The trellis for an example boundary is shown in Fig. 1. Based on the trellis, the hidden states of the HMM is defined by the nodes along the boundary normals. The observations are defined by the external local costs (complex wavelet phase coherence moments) and internal local costs (first-order elastic and second-order membrane constraints). The main advantage to formulating the boundary extraction problem using a HMM is that the solution to the problem can be found in a very efficient manner using methods such as the Viterbi algorithm [12]. This is as opposed to existing IS methods, where the problem formulation does not allow such a solution. Computational efficiency is very important for the proposed EIS algorithm since the underlying goal is to provide fast user interaction for clinicians.

D. Second-order Viterbi Boundary Optimization

The third and final step of EIS is to solve the HMM formulated in Section II-C. As described in the previous section, a highly efficient method for solving the proposed HMM is the Viterbi algorithm. While the Viterbi algorithm is highly efficient, it can become slow for situations where a large number of states exist in the HMM. This is particularly problematic in the case of complex boundaries where a large number of nodes are needed to represent the boundary properly. Therefore, a

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novel phase-based adaptive state pruning scheme is introduced to improve the computational performance of EIS. At the seed point of the boundary, a global threshold τ_g is applied to the initial states of the HMM based on the extracted phase coherence moments. States that fall below the τ_g are pruned from the HMM. As we move along the states in the HMM, the threshold is adaptively adjusted based on the first-order Markov assumption:

$$\tau_s = \frac{\sigma_{s-r}\mu_{s-r} + \sigma_s\mu_s}{\sigma_{s-r} + \sigma_s} \tag{2}$$

$$\tau_0 = \tau_g \tag{3}$$

where s is the current point, r is a fixed interval, σ_{s-r} and μ_{s-r} are the variance and mean of phase moments from prior points to the point $s-r$ respectively, and σ_s and μ_s are the variance and mean of phase moments from point $s-r$ to the point s respectively. In this manner, states that have a low probability of residing on the boundary are pruned from the HMM. In best case scenario, the number of states in the HMM can be reduced from pq to q, thereby substantially reducing the computational complexity of the proposed algorithm.

In conventional IS algorithms, only the first-order elastic constraints are considered. The major drawback to accounting for the first-order elastic constraints is it does not penalize spurious edges. This is particularly problematic for medical images, where such spurious edges often arise due to signal noise. To address this issue, the proposed algorithm also accounts for second-order membrane constraints. Since both first-order and second-order constraints are considered in the EIS algorithm, a second-order Viterbi algorithm must be used to evaluate the partial hypothesis of each state of the HMM. Let V be a matrix containing all nodes within the trellis:

$$V = \{\underline{v}_1, \underline{v}_2, \quad . \quad . \quad . \quad , \underline{v}_i, . \quad . \quad . \quad , \underline{v}_q \;\} \tag{4}$$

where $\underline{v}_i$ is a column vector representing the i^{th} normal along the boundary $\underline{v} = [\underline{x}, \underline{y}]$. To incorporate second-order membrane constraints into the trellis, it is necessary to design a second-order Viterbi approach where the present state not only depends upon the previous state but also the state before that. However, modifying the Viterbi algorithm to incorporate second-order Markovian assumptions is difficult. To overcome this problem, the approach taken by the proposed method is to modify the trellis rather than the Viterbi algorithm itself to incorporate second-order Markovian assumptions. This allows the conventional Viterbi approach to be used to compute the partial hypothesis at each node based on both first-order elastic and second-order membrane constraints. Suppose we have n hidden states and we are observing the states q times, as shown in Fig. 2(a). Consider that the partial hypothesis of a state at i depends upon states at $i-1$ and $i-2$. One can reformulate the trellis by combining the states at i with states at $i-1$ and states at $i-1$ with states at $i-2$. The resulting trellis contains n^2 hidden states and $q-1$ observations as shown in Fig. 2(b). In this way, the partial hypothesis of the modified trellis will depend only upon the previous states without violating first order Markovianity.

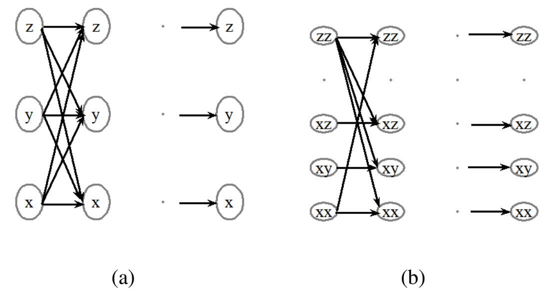

Fig. 2. Reformulating the second-order Viterbi problem with first-order Markovian assumptions: a) original trellis, and b) modified trellis.

Based on the modified trellis, the partial hypothesis at each node can be computed as follows. The probability of the states at each node of the trellis is denoted as the confusion matrix ($B = b_{ij}$) and is computed from the extracted phase coherence moments. The state transition matrix ($A = a_{ij}$) is computed from the first-order elastic and second-order membrane constraints. The initial state probabilities ($\Pi = \pi_i$) are also computed from the extracted phase coherence moments. Given the triplet $[\Pi, A, B]$, the Viterbi algorithm with first order Markovian assumptions is used to compute the partial probability at each state. The states which maximizes the likelihood of their next state are considered to be the best hypothesis for that observation sequence. Based on this, the most likely sequence of hidden states for an observation sequence can be found. In our case, this sequence of hidden states forms the optimal boundary around the region of interest between two user-defined points. Utilizing the Viterbi algorithm with state pruning provides an advantage in computational efficiency. The EIS has a complexity ranging from order q to pq, whereas the conventional IS utilizes a modified Dijkstra's Algorithm [5], with computational complexity on the order p^2q^2. Therefore, the increase in speed makes EIS more suited to real-time user interaction.

III. Experimental Results

To illustrate the effectiveness of the proposed EIS method in segmenting medical images, six medical images test cases derived from the Visible Human project (VHP) and Whole Brain Atlas [13] (WBA) are used. A summary of each test case is given below.

1) **Test 1**: Head, sagittal, MR T1; ROI: cerebellum, WBA.
2) **Test 2**: Torso, axial, MR T1; ROI: pleural cavity, VHP.
3) **Test 3**: Torso, coronal, CT; ROI: pleural cavity, VHP.
4) **Test 4**: Head, transverse, ultrasound; ROI: aneurysm.
5) **Test 5**: Lumbar, sagittal, fluoroscopy; ROI: vertebrae.

To perform the segmentation using Enhanced Intelligent Scissors, user-defined points were chosen near the boundary of interest, but in an inexact manner such that they do not fall on the boundary exactly. The Intelligent Scissors method proposed by Mortensen et al. [5] was evaluated for comparison purposes. To evaluate segmentation accuracy in a quantitative manner, the normalized MSE between the ground truth contour and the obtained contours using the conventional IS method

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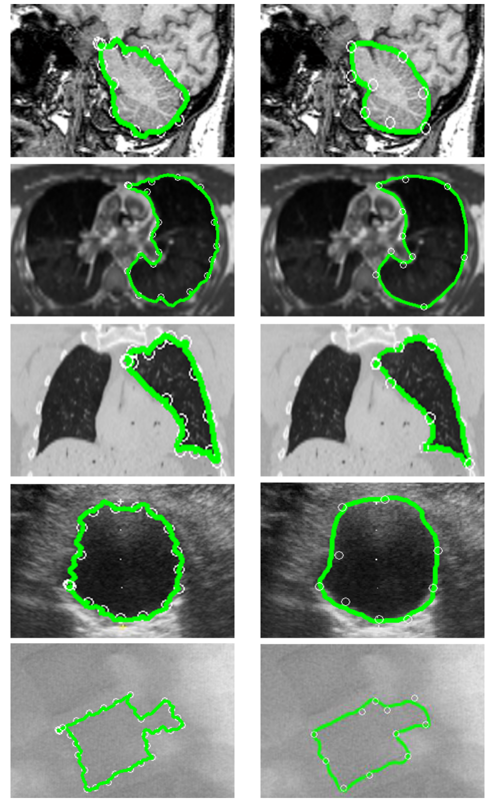
and the proposed EIS method is computed for each test case on a per-pixel basis. Usability tests were also conducted by measuring the amount of time a user requires to segment each image using both methods. A total of 5 trials were conducted by 5 different users for each image, and the results were averaged.

A summary of experimental results is shown in Table I. The segmentation results for all tests are shown in Fig. 3, in which the user-defined points for IS and EIS are overlaid. It can be observed that the proposed EIS method produced very accurate boundaries around the regions of interest. The MSE is comparable for all cases, despite the fact that EIS uses fewer user-defined points, while also requiring less computation time. Also note that the user-defined points for EIS can deviate from the boundary, whereas all the user-defined points in conventional IS must fall on the boundary exactly. Visually, it can be seen that the segmentation produced by EIS is smoother, despite the fact that fewer user-defined points are used. It can also be seen that an accurate segmentation is obtained for both the ultrasound (Test 4) and fluoroscopy (Test 5) cases, which are highly contaminated by noise and contrast non-uniformity. The usability tests indicate that the user interaction time for EIS is significantly lower than that for IS in all test cases. From these results, it can be observed that the proposed EIS algorithm can be used effectively for the purpose of rapid medical image segmentation.

TABLE I
SEGMENTATION ACCURACY

Test Set	MSE[1] (pixels)		User points[1]		User Time[1] (s)	
	IS	EIS	IS	EIS	IS	EIS
TEST1	3.15	2.30	14	8	29.3	14.5
TEST2	3.58	3.54	19	11	26.7	15.1
TEST3	1.75	1.66	18	6	12.4	7.4
TEST4	2.49	2.16	19	8	17.4	8.3
TEST5	3.62	2.98	27	11	30.5	10.9

[1]The results are computed as the average over 25 trials.



(a) (b)

Fig. 3. Segmentation results for Tests 1, 2, 3, 4, and 5: (a) IS, and (b) EIS. It can be seen that EIS produced accurate boundaries in all cases without requiring accurate manual tracing of the boundary. The circles denote the user-defined points.

IV. CONCLUSIONS AND FUTURE WORK

In this paper, we introduced Enhanced Intelligent Scissors (EIS), a novel fast interactive approach to medical image segmentation. The proposed algorithm is highly robust to contrast non-uniformities and noise through the use of an external local cost based on complex wavelet phase coherence moments. The optimal boundary between user-selected points is found by formulating the problem as a HMM and solved using a novel approach to the second-order Viterbi algorithm. Furthermore, a novel phase-adaptive state pruning scheme was proposed to improve the computational performance of the proposed algorithm. Experimental results show that a high level of segmentation accuracy can be achieved for medical images without requiring accurate manual tracing like existing semi-automatic segmentation methods. Future work involves extending the proposed method for interactive 3D segmentation, which is very important for volume segmentation in medical images.

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