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COMBINING ATLAS AND ACTIVE CONTOUR FOR AUTOMATIC 3D MEDICAL IMAGE SEGMENTATION

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Abstract

Atlas based methods and active contours are two families of techniques widely used for the task of 3D medical image segmentation. In this work we present a coupled framework where the two methods are combined together, in order to exploit each's advantage while avoid their respective drawbacks. Indeed, the atlas based methods lacks the flexibility in locally tuning the segmentation boundary; whereas the active contour has the drawback that the final result heavily depends on the initialization as well as the contour evolution energy functional. Therefore, in the proposed work, the atlas based segmentation provides a probability map, which not only supplies the initial contour position, but also defines the contour evolution energy in an on-line fashion. Afterward, the active contour further converges to the desired object boundary. Finally, the method is tested on various 3D medical images to demonstrate its robustness as well as accuracy.

Index Terms

Atlas based segmentation; Active contour segmentation

1. INTRODUCTION

Atlas based methods and active contours are two families of techniques widely used for the task of 3D medical image segmentation. Indeed, the atlas based methods utilize the registration techniques to solve the segmentation problems. They are robust to image noise, and the final shape usually does not deviate very much from the training shapes. However, it often lacks the flexibility in locally fine tuning the object boundaries[1, 2, 3]. On the other hand, capturing the local shape features is a common capability for the active contour method. Nevertheless, due to the fact that the contour is driven by a pre-defined segmentation energy functional in a variational manner, its convergence is local. Not only does this cause the sensitiveness to the initialization, but also the shape of the object may not be well preserved. Furthermore, the pre-defined segmentation energy function may not be well representing the object characteristics in the present image[4, 5]. In table 1, the aforementioned advantages/disadvantages are summarized.

Given the advantages and disadvantages of the two categories of methods, a logical expectation is to exploit the advantages while avoid the disadvantages. For that purpose, in this work we present a coupled framework where the two methods are combined. Specifically, the atlas based segmentation computes an initial probability map, which not only provides the initial contour position, but also defines the contour evolution energy in an on-line fashion. That is, the characteristics of the target in the present image can be learned

and the contour evolution energy functional can then be designed accordingly. Consequently, the active contour is further driven by such adapted energy, together with shape constraint, and converges to the desired object boundary.

In the remainder of the paper, the proposed method is presented in Section 2, and the experiments are conducted with their results analyzed in Section 3. Finally, the paper is concluded in Section 4.

2. METHODS AND IMPLEMENTATION

In this section, we present the coupled framework of atlas based segmentation and shape based active contour segmentation. More explicitly, in Section 2.1, the multi-atlas based segmentation is employed to generate an initial probability map. Based on that, in Section 2.2, the object characteristics in the target image is being learned and the accordingly designed active contour evolution is carried out for extracting the final boundary of the object.

2.1. Probability Map Generation

As the input for the atlas based segmentation, a set of N grayscale training images: $J_1, J_2, \dots, J_N: \mathbb{R}^3 \rightarrow \mathbb{R}$ are provided for the algorithm, along with their corresponding label maps: $U_1, U_2, \dots, U_N: \mathbb{R}^3 \rightarrow \{0, 1\}$ in which the object is labeled by 1. Furthermore, the novel image to be segmented is denoted as $I: \mathbb{R}^3 \rightarrow \mathbb{R}$.

In order to provide the probability map for the subsequent active contour segmentation, the N training images are deformably registered to the novel image. More explicitly, for each $i \in 1, \dots, N$, an affine transformation, $\mathcal{T}_A^{(i)}$, is computed in order to minimize the mutual information between J_i and I [6]. It is noted that due to the usage of the mutual information, the training images and the novel image may be of different modalities. After that, a

deformable transformation $\mathcal{T}_B^{(i)}$, parametrized by B-Splines, is computed between the

$J_i \circ \mathcal{T}_A^{(i)}$ and I , and the final registration cost functional value c_i is recorded. With the transformations obtained, the corresponding label map U_i is transformed as

$U_i \circ \mathcal{T}_B^{(i)} \circ \mathcal{T}_A^{(i)} =: V_i: \mathbb{R}^3 \rightarrow \mathbb{R}$. Next, the $V_i; i = 1, \dots, N$ images need to be fused to form a

single probability map. To that end, a weighted sum of V_i 's are computed as $P := \sum_i^N \omega_i V_i$,

where the weighting coefficients ω_i 's are computed as $\omega_i = \beta_i / \sum_i^N \beta_i$ with $\beta_i = \exp(\gamma(\min(c_i) - c_i))$, in which γ is chosen such that $\exp(\gamma(\min(c_i) - \max(c_i))) = 0.1$.

As of the implementation, in order to mitigate the error resulting from the implementation, we opt to use the registration schemes found in the InsightToolkit [7]. Finally, the probability map P computed above will be used in the subsequent shape based active contour evolution scheme.

2.2. Object Characteristics Identification and Shape Based Active Contour Segmentation

Some atlas based methods stop at the end of the above section and output certain level contour, e.g. the 0.5 level contour, of P as the final segmentation. However, from the probability map P , one can further extract the information in the novel image, and automatically adapt the active contour method to achieve better accuracy. Indeed, in this section we show how the image characteristics of the object in the novel image is learned, and how the active contour evolution further improves the final results.

2.2.1. Object Characteristics Identification—Most of the active contour evolutions are driven by the pre-defined energy functional, such as high image gradient, prominent average intensity difference across the boundary, etc[4, 5]. While in many cases they do reflect certain aspects of the object, nevertheless, they are not universally suitable. To solve that problem, in the proposed framework, the probability map P is further utilized in order to tailor the active contour segmentation process to reflect the current object characteristics in an adaptive fashion and achieve better segmentation results. Indeed, although the level curve of P may not be satisfying as the final output, however, the assumption that the “core-region” of the P , defined as $\Omega := \{\mathbf{x} \in \mathbb{R}^3 : P(\mathbf{x}) \geq 0.8\}$ being inside the object, is usually valid. Based on that, the characteristics of the target can be learned by a non-parametric kernel density estimation [8].

Formally, for each $\mathbf{x} \in \Omega$ three robust statistics of the image intensity, namely the inter-quartile range ($IQR(\mathbf{x})$), median ($MED(\mathbf{x})$), and the median absolute deviation ($MAD(\mathbf{x})$) are computed in the 26-neighborhood $B_{\mathbf{x}}$ around $\mathbf{x}$. They form the characteristics vector at $\mathbf{x}$ defined as $\mathbf{f}(\mathbf{x}) := (IQR(\mathbf{x}), MED(\mathbf{x}), MAD(\mathbf{x}))^T \in \mathbb{R}^3$. Furthermore, the distribution of the characteristics vectors is computed as $p(\mathbf{f}) = \sum_{\mathbf{x} \in \Omega} K_{\eta}(\mathbf{f} - \mathbf{f}(\mathbf{x})) / |\Omega|$, where K is the kernel function. In this work, we use the Gaussian kernel. Its variance is chosen to be 0.1 times the MAD of the seed group, and we have found that this works for all the cases tested.

2.2.2. Shape learning—In order to prevent the evolving active contour deviate from the desired shape, it is common to impose shape prior in the evolution[9, 10, 11, 12]. To that end, the shape of the target object need to be learned. Specifically, the training shapes $U_i; i = 1, \dots, N$ are first registered to minimize the mean square error over the similarity transformation, and the registered shapes are denoted as $S_i; i = 1, \dots, N$. Then, the standard PCA is adopted to statistically learn the shapes: The mean shape is computed as

$\bar{S}(\mathbf{x}) = \frac{1}{N} \sum_{i=1}^N S_i(\mathbf{x})$ and is subtracted from each shape, i.e. $\tilde{S}_i = S_i - \bar{S}$. Since each S_i is a 3D volume, we can concatenate the rows to form a long vector η_i . Then the covariance matrix is formed as $C = (\eta_1, \dots, \eta_N) (\eta_1, \dots, \eta_N)^T / N$ and the singular value decomposition gives $C = G \Lambda G^T$, where Λ is a diagonal matrix containing the eigenvalues and the columns of G store the eigenvectors. Note that these are reshaped to the original image size and are denoted as $g_i(\mathbf{x})$. Usually, only the eigen-shapes corresponding to the first L eigenvalues are kept while the others (with smaller eigenvalues) are ignored. Hence, the shape prior is a space spanned by $\{g_i : 1, \dots, L\}$. In the subsequent segmentation, the shape is constrained to lie within this space. In order to balance the accuracy and computation time, in all our experiments, we set $L = 6$.

2.2.3. Shape Based Robust Statistics Segmenter—At this point, we are able to apply the shape based active contour segmentation based on the robust statistics distribution learned in Section 2.2.1 as well as the shape prior information in Section 2.2.2. To that end, we first denote the evolving closed contour (closed surface in 3D) to be $C : [0, 1]^2 \times \mathbb{R}^+ \rightarrow \mathbb{R}^3$. Moreover, the contour evolves in a variational framework where an energy functional is associated with the current contour and is defined as:

$$E(C) := - \int_{\mathbf{x} \in C} p_i(\mathbf{f}(\mathbf{x})) d\mathbf{x} + \theta \int_C ds \quad (1)$$

where $\theta > 0$ is a smoothness factor. Moreover, the 0.5 level curve of the probability map P is used as the initial position of the contour. Therefore, computing the first variation of the energy we have the contour evolution as an initial value problem:

$$\begin{cases} \frac{\partial C(t)}{\partial t} = [-p(C(t)) + \lambda \kappa(t)] \mathbf{N}(t) \\ C(0) = \{\mathbf{x} \in \mathbb{R}^3 : P(\mathbf{x}) = 0.5\} \end{cases} \quad (2)$$

in which $\mathbf{N}$ is the inward unit normal vector field on C and κ is the mean curvature of the contour (surface).

However, with not perfect image quality, the above data-driven contour evolution usually suffers from under-segmentation or leakage. To cure that, we filter the shape in order to make it fall into the admissible shape space learned in Section 2.2.2. To this end, by noticing that the shape space learned is associated with certain spacial position, first of all, the binary volumetric representation W of the current contour is computed as $W(\mathbf{x}) = 1$ if and only if $\mathbf{x}$ is inside C . Secondly, W is registered to the mean shape $S(\mathbf{x})$ by minimizing the mean square error over the similarity transformation $\mathcal{T}_s$, and the mean shape is then removed from the registered W , denoted as $\tilde{W} := W \circ \mathcal{T}_s - S$. In order to project $\tilde{W}$ into the learned shape space, by noticing that $\{g_i; i = 1, \dots, L\}$ is a set of basis for the shape space, the coefficients of $\tilde{W}$ in such basis is computed as:

$$\alpha = \left(\tilde{W} \cdot g_k / \sqrt{\lambda_k}; k=1, \dots, L \right)^T \quad (3)$$

where λ_k is the k -th diagonal element of Λ .

By the Gaussian assumption of the principle component analysis, the larger the $\|\alpha\|$ is, the less probable such realization would emerge. Therefore, in order to pull the present shape into the learned shape space, as well as preserving its unique shape features, the coefficient $\|\alpha\|$ is adjusted as:

$$\tilde{\alpha} := \begin{cases} \alpha, & \|\alpha\| \leq 6 \\ 6\alpha / \|\alpha\|, & \|\alpha\| > 6 \end{cases} \quad (4)$$

In Equation (4), if the coefficient lie outside the hyper-sphere with radius of 6, then it is pulled back onto the 6-hyper-sphere. The 6 is chosen because a sample which is 6 standard deviations away is very rare. The adjusted coefficient $\tilde{\alpha}$ is then used to reconstruct the “filtered shape” $\hat{W}$ as:

$$\hat{W} := (g_1, \dots, g_L) \text{diag}(\sqrt{\lambda_1}, \dots, \sqrt{\lambda_L}) \cdot \tilde{\alpha} + \bar{S} \quad (5)$$

and the “filtered shape” is transformed back to its previous pose using $\mathcal{T}_s^{-1}$. And $\hat{W} \circ \mathcal{T}_s^{-1}$ is then used as the initial segmentation contour for the next-round data driven segmentation. These two steps (data driven and shape filtering) alternate until convergence. Usually, it only takes two or three iterations for convergence on the data sets we used.

3. EXPERIMENTAL RESULTS

In this section, we present the experiments of using the proposed method in extracting prostate and caudate nucleus from MR images.

3.1. Prostate segmentation

30 data sets from 15 patients are downloaded from on-line publicly available repository¹. Each patient has both T1 and T2 MR prostate images from a 1.5T MR scanner. However, given that only the expert segmentations for T2 images are provided, in order to compare

with the expert segmentation, we opted to segment these 15 T2 images. The ages of the patients range from 50 to 80 with a mean at 63.7. After applying the proposed method (leave-one-out scheme), one randomly chosen result is shown in Figure 1.

Furthermore, the Dice coefficients with respect to the expert segmentation results given on the web site are provided in Table 2.

3.2. Caudate segmentation

29 sets of MRI data sets were collected and manually segmented by radiologist at the Brigham and Women's Hospital. The patient ages ranged from 22 to 56 with a mean of 38.9.

Similarly, the proposed method is applied (leave-one-out scheme) on all the 29 data sets and the Dice coefficients are obtained in Table 3.

4. CONCLUSION

In this work we present a coupled framework where the atlas based method and active contour methods are combined, in order to exploit each's advantage while avoid their respective drawbacks. In doing so, the atlas based segmentation provides a probability map, which not only supplies the initial contour position, but also defines the contour evolution energy in an on-line fashion. Afterward, the active contour further converges to the desired object boundary. The experiments are conducted for the MR prostate and head images to demonstrate its robustness as well as accuracy.

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¹http://wiki.na-mic.org/Wiki/index.php/Training_Data_Prostate_Segmentation_Challenge_MICCAI09

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Fig. 1.
Segmentation result of one prostate data set.

Table 1

(Dis)advantages of atlas and active contour methods.

	Pros	Cons
Atlas based	<ul style="list-style-type: none"> • Robust • Preserve shape 	<ul style="list-style-type: none"> • Miss local shape feature
Active contour	<ul style="list-style-type: none"> • Capture local shape feature 	<ul style="list-style-type: none"> • Sensitive to initialization • Shape not preserved

Dice coefficients for the T2 prostate images. It is noted that the patient IDs are taken from the clinical study and they are not contiguous.

Table 2

Patient ID	29	35	36	41	45	49	54	55	56	60	64	69	73	85	88	Mean	STD
Dice Coef $\times 10^2$	83	79	76	75	70	82	83	76	80	70	82	79	82	79	78	79	4

Table 3

Dice coefficients for the caudate segmentation.

Patient ID	1	2	3	4	5	6	7	8
Dice $\times 10^2$	79	79	83	85	85	75	80	73
Patient ID	9	10	11	12	13	14	15	16
Dice $\times 10^2$	74	79	87	76	81	78	85	74
Patient ID	17	18	19	20	21	22	23	24
Dice $\times 10^2$	80	82	85	87	80	72	76	74
Patient ID	25	26	27	28	29	Mean		STD
Dice $\times 10^2$	90	76	83	79	84	81		5