

ESTIMATING PATIENT-SPECIFIC SHAPE PRIOR FOR MEDICAL IMAGE SEGMENTATION

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ABSTRACT

Image segmentation is one of the key problems in medical image analysis. This paper presents a new statistical shape model for automatic image segmentation. In contrast to the previous model based segmentation methods, where shape priors are estimated from a general population-based shape model, our proposed method aims to estimate patient-specific shape priors to achieve more accurate segmentation by using manifold learning techniques. The proposed shape prior estimation method is incorporated into a deformable model based framework for image segmentation. The effectiveness of the proposed method has been demonstrated by the experiments on segmenting the prostate from MR images.

Index Terms— image segmentation, shape modeling, manifold learning

1. INTRODUCTION

Image segmentation is an important processing step in medical image analysis, which divides an image into a number of disjoint regions such that the pixels in each region denoting an anatomical or a meaningful part of it. Since manual segmentation is a tedious and time consuming procedure, automated segmentation is much desired in many applications. A large variety of different segmentation methods have been proposed in the past. Roughly, the existing methods can be divided into three kinds of methods, region based segmentation methods [1], boundary segmentation techniques [2], and model-based methods like active shape model (ASM) [3] and active appearance model (AAM) [4].

Among the above three categories of the segmentation algorithms, the ASM introduced by Cootes *et al.* [3] has obtained considerable success for its ability to incorporate shape prior information extracted from a set of training images and its flexibility to compactly represent object shapes. ASM consists essentially of a statistical shape model (SSM) and a model deformation strategy. In its SSM part, principal component analysis (PCA) is used for dimensionality reduction and shape modeling. However, PCA is most useful in the cases where all the shapes lie in or at least approximately

linear subspace of the data set. Nevertheless, this is not often the case. It is very likely that some important information can be lost, if we represent non-linear data using a linear approach. This problem may largely influence the accuracy of shape prior estimation.

As a nonlinear dimensionality reduction technique, manifold learning based algorithms [5] essentially attempt to duplicate the behavior of PCA, but nonlinearly mapping shapes onto manifolds instead of linear subspaces. Recently, Etyngier *et al.* [6] employed shape prior manifold for shape modeling to guide image segmentation. However, their work is constrained by the triangulation of manifold space and only the shapes projected onto the three vertices surrounding the target shape can be used, which limits its ability to approximate the patient-specific shape for segmenting the target image.

In this paper, we propose a new method to estimate patient-specific shape priors to achieve more accurate segmentation by using manifold learning. The training shapes are first mapped to an embedded lower dimensional manifold, where only the main nonlinear local variation between the shapes is preserved. When doing image segmentation, instead of directly estimating the shape prior in the training shape space, the obtained object contour is also projected into the manifold space and its closest training shape neighbors in this subspace are retrieved. By computing the weighting coefficients of the neighbors for approximating the projected shape in the low dimensional space, a patient-specific shape prior can be generated by combining the corresponding training shapes in the original shape space using the same coefficients. The proposed shape prior estimation method is then incorporated into a deformable model based framework for image segmentation.

The rest of the paper is organized as follows. In Section 2, the method of learning shapes on manifold is presented. In Section 3, the proposed model based segmentation is provided in detail. In Section 4, a series of experiments are conducted to validate the performance of the proposed method. The paper is concluded in Section 5.

2. ESTIMATING PATIENT-SPECIFIC SHAPE PRIOR

The larger the number of samples in the training set may not always be the better, since the learned population-based shape statistics may generate “blurred” shape prior when segmenting an image of a particular subject. Ideally, patient-specific shape statistics should be used. However, such patient-specific model is usually not available. In this work, we propose to select training shapes, which are close to the target shape of the subject on a lower dimensional manifold, to approximate the patient-specific shape prior. The reasoning behind our work is that the manifold learning can preserve the local structure of the image space, while PCA aims to preserve the global structure of the image space. In many real-world classification problems, the local manifold structure which is modeled by a nearest-neighbor graph is more important than the global Euclidean structure.

2.1. Construction of shape manifold

In our work, a shape is described by n landmark points $(x_1, y_1) \cdots (x_n, y_n)$ forming a shape vector $S = (x_1, y_1, \cdots, x_n, y_n)^T$. The landmark points are obtained by sampling the contour equally Euclidean distance spaced. Each $2n$ dimensional shape vector is then mapped to m dimensional manifold for shape learning and prior estimation, where $m \ll 2n$. Most manifold learning algorithms, such as Locally Linear Embedding (LLE) and Isometric Feature Mapping (ISOMAP), assume that a set of high-dimensional input data may generate a low-dimensional manifold. In other words, the low-dimensional manifold can maintain the most important features in the original input space. Most of these techniques construct an adjacency graph of the learning samples and map the data points into a lower-dimensional space, while preserving the local properties of the adjacency graph. In our work, the same approach is employed. Our method of shape manifold learning is described as follows, which is adapted from the ISOMAP algorithm [6].

- Project the learning set of shape samples $\{S_i\}$ into manifold subspace by minimizing Lost Function, which measure the difference between the estimated value and the true value. In our experiments, 96 percent information is kept in the sense of reconstruction error. The variation of local information that is kept on local structure in the manifold subspace, is crucial to guide the segmentation.
- Construct the adjacent graph as shown in Fig. 1. Let G denote a graph with n vertices. The i th vertex s_i corresponds to the shape S_i in the original shape space. Find the geodesics (=shortest paths on the graph) between all pairs of vertices by Dijkstra’s algorithm.

$$d_{ij} = \arg \min_i \sum_j g(s_i, s_j) \quad (1)$$

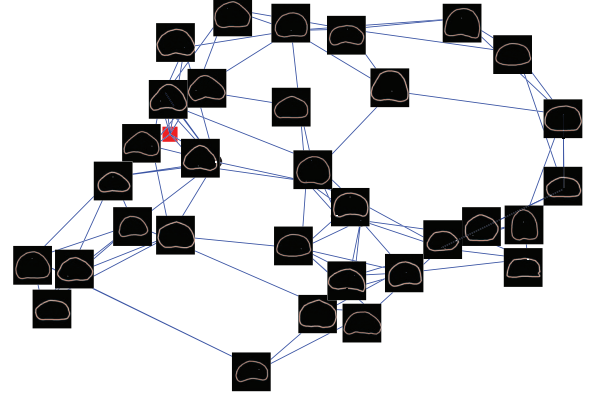


Fig. 1. Two-dimensional embedding of the manifold of training shapes. Note that only a subset of the samples is shown to avoid clutter.

where g is the length of the shortest path, s_i and s_j denote the corresponding shape after manifold.

- Construct the nearest-neighbor graph by connecting k -Nearest Neighbor (k NN) for each shape based on the edge lengths. The constructed nearest-neighbor graph is an approximation of the local manifold structure.

The size of the neighborhood k in k NN is a parameter that is selected by user. The value of k should be set appropriately. If the value is too small, there may be multiple disjoint sub-graphs. An extremely large value can make the adjacent graph to become completely connected. In this paper, the value of k is offset heuristically based on the experimental results.

It can be seen from Fig. 1 that on manifold, the shape (denoted by the red square) can be represented approximately by the k nearest neighbors.

2.2. Shape prior estimation

By using the learned manifold, we can estimate the shape prior for an image to be segmented by choosing a certain amount of training shapes, which are closest to the currently obtained shape. Let $N(i)$ denote the neighborhood containing the k NNs of a shape s_i on the learned manifold. The shape S_i can then be represented by a weighted convex combination of the shapes in $N(i)$. The weights are chosen to minimize the following squared error for each i :

$$\xi(W) = \arg \min_i \left\| \sum_{j=1}^k w_j^{(i)} \right\|^2. \quad (2)$$

The weight $w_j^{(i)}$ balances the contribution of the j th shape to the i th reconstruction. There are some constraints on the weights: $\sum_j w_j^{(i)} = 1$ and $w_{ij} = 0$ if $j \notin N(i)$. There is a closed form solution for w , which can be derived using Lagrange multipliers. In particular, if $j \in N(i)$, the reconstruction weight for each shape s_i (the projection of S_i on the

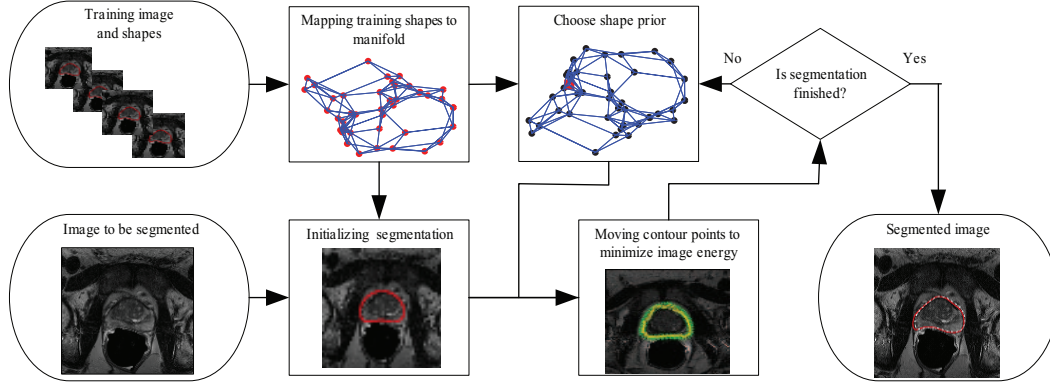


Fig. 2. Flow chart of the proposed method.

low-dimensional manifold) is given by $w_j^{(i)} = e^{-\frac{d_{ij}}{\sigma}}$, where σ is a suitable constant, otherwise put $w_j^{(i)} = 0$. The weight matrix W of graph G models the shape manifold structure by preserving local structure.

Using the idea of Chang *et al.* [7], the shape in the high-dimensional space is computed using appropriate high-dimensional features of the k nearest neighbors and the reconstructed weights. The estimated shape prior is given by

$$\hat{S}_i = \sum_{j=1}^k w_j^{(i)} S_{N(j)}, \quad (3)$$

where \hat{S}_i can be linearly reconstructed in terms of its neighbors $S_{N(1)}, \dots, S_{N(k)}$ with corresponding weight $w_j^{(i)}$. Since the weight $w_j^{(i)}$ is the similarity measure between S_i and its neighbors $S_{N(1)}, \dots, S_{N(k)}$, the obtained shape is patient-specific.

3. MODEL BASED SEGMENTATION

Our proposed shape prior estimation method is incorporated into a model based segmentation framework for medical image segmentation as shown in Fig. 2. First, the segmentation is initialized by the average of training shapes. Then we project the initialized shape to the same manifold with the training shapes. Secondly, we choose shape prior through the nearest-neighbor graph. Thirdly, the shape prior is seen as initialization and the contour points are moved to minimize image energy. The above steps will be repeated until a satisfactory result is obtained. The details of the proposed segmentation method are presented as follows.

Similar to ASM [3], the deformable model has two terms in its energy functional

$$E = E_{image} + E_{shape}. \quad (4)$$

The segmentation is achieved by minimizing the above energy in an iterative way [8]. Each iteration contains two steps

to minimize the image energy and shape energy terms, respectively. The two steps are described in detail as follows.

- Image energy minimization

1. Examine a region of the image around each landmark point S_i to find the best nearby match for the point S'_i .
2. Update the parameters (X_t, Y_t, s, θ) to best fit the new found points S

In practice, we look along the normal directions of the contour at each landmark point to find the object boundary. S is a shape vector containing n landmark points. The parameters (X_t, Y_t, s, θ) represent x -axis shift (right), y -axis shift (down), scale, rotation. Human-machine interaction is used to adjust parameters.

- Shape energy minimization

1. Map the current contour S_i obtained at the i th iteration to the same manifold space with the training shapes. The projected shape is denoted by \hat{s}_i .
2. Compute the geodesic distance between each training shape and \hat{s}_i .
3. Select training shapes according to \hat{s}_i using k NN algorithm on the adjacent graph.
4. Project the step 3 result onto the original space and apply equation (3) to achieve \hat{S}_i .

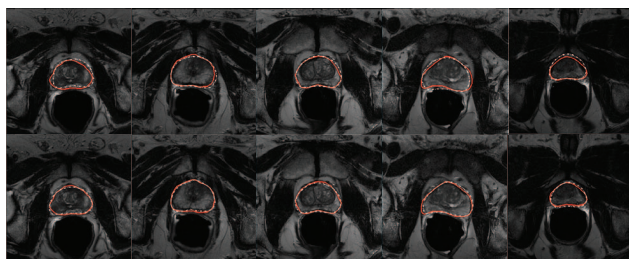
In our work, the segmentation is initialized by using the mean shape computed from the training shapes.

4. EXPERIMENTS

We evaluated the performance of the proposed method on 42 MR images of the prostate. The manually delineated prostate contours by a radiologist were considered as gold standard for validation. In our experiments, each image contains 512x512 pixels, with the pixel size of 0.3mmx0.3mm. As the number of the sample was relatively limited, cross validation with a

Table 1. Parameters used in the experiments.

symbol	Values and Description
n	64(Number of contours points used to match the prostate field)
I	50(Maximum number of iterations)
k	Number of the closest shape statistics to patient-specific shape

**Fig. 3.** Segmentation results of the ASM method (top row) and our method (bottom row), together with corresponding manual segmentation. The solid red contours represent the manual segmentation results and the dashed white contours denote the segmentation results obtained using our proposed method.

leave-one-out strategy was applied. At each time, one of the 42 images was used for testing and the prostate shapes from the other 41 images were used for training.

Before providing the detailed experimental results, we first summarize the parameters used in these experiments, as shown in Table 1. The effects of the different values of parameter k on the segmentation results are shown in Table 2. Our method was implemented using Matlab. The computation time for segmenting one prostate MR image is around 60 s on a 3.0Ghz Intel PC with 2GB RAM.

Fig.3 presents a series of examples of the prostate segmented using both our proposed method and ASM [3] together with the ground truth, for visual comparison. It can be seen that segmentation based on our proposed method is much better than segmentation based on the ASM method and visually as good as manual segmentation. The performance of method was quantitatively evaluated by the average distance between the automatic segmentation results and the manual segmentation. The segmentation results of ASM are also included for comparison. The evaluation results are given in Table 3. It can be seen that the average contour distance for our method is about 5.2 pixels (1.56mm) compared to 7.25 pixels (2.17mm) for the ASM method.

5. CONCLUSION

In this paper, we present a novel segmentation method, which incorporates the shape prior on manifold. The proposed approach has been evaluated on prostate MR images. The experimental results are promising and show our algorithm can out-

Table 2. The impact of different values of parameter k on the segmentation results.

value of k	5	10	15	20	25	30	35
distance(mm)	1.7	1.49	1.31	1.83	1.91	1.94	1.9

Table 3. Average contour distance between the manual segmentation and the automated segmentation of the 42 images.

Algorithm	metric	Mean \pm std	Min	Median	Max
ASM	pixel	7.25 ± 1.7	4.99	7.25	12.76
	mm	2.17 ± 0.5	1.44	2.07	3.82
Our method	pixel	5.2 ± 1.11	3.68	5.23	8.79
	mm	1.56 ± 0.33	1.1	1.56	2.63

line the prostate boundary from these MR images accurately, compared to the manual segmentation. It can also achieve better segmentation results than the ASM method. In our future work, we will investigate the ways to speed up the segmentation process.

6. ACKNOWLEDGEMENT

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7. REFERENCES

- [1] P. Yan and A. A. Kassim, "Segmentation of Volumetric MRA Images by Using Capillary Active Contour," *Medical Image Analysis*, vol. 10, No. 3, pp. 317-329, June 2006.
- [2] A. A. Kassim and P. Yan, "Medical Image Processing," *Encyclopedia of Computer Science and Engineering*, B.W. Wah (ed.), John Wiley & Sons, New Jersey, 2008.
- [3] T. F. Cootes, C. J. Taylor, D. H. Cooper, and J. Graham, "Active shape models - their training and application," *Computer Vision and Image Understanding*, vol. 61, no. 1, pp. 38-59, 1995.
- [4] T. F. Cootes, G. Edwards, and C. J. Taylor, "Advances in active appearance models," *In Proc. International Conference on Computer Vision*, pp. 137-142, 1999.
- [5] J. B. Tenenbaum, V. de Silva, and J. C. Langford, "A global geometric framework for nonlinear dimensionality reduction," *Science*, vol. 290, pp. 2319-2323, 2000.
- [6] P. Etyngier, Ségonne and R. Kwiven, "Shape Prior using Manifold Learning Techniques," *in Proc. IEEE International Conference on Computer Vision*, vol. 15, pp. 132-141, Oct 2007.
- [7] H. Chang, D. Yeung, and Y. Xiong, "Super-resolution through Neighbor Embedding," *CVPR*, pp. 1167-1183, 2004.
- [8] J. Hamm, D. H. Ye, R. Verma, and C. Davatzikos, "GRAM: A framework for geodesic registration on anatomical manifolds," *Medical Image Analysis*, vol. 14, pp. 633-642, 2010.