REGION-BASED APPROACH FOR DISCRIMINANT SNAKES

ABSTRACT

This paper proposes a statistic framework for segmenting textured areas over real images by discriminant snakes. Our active contour model has the ability to learn different texture prototypes and generate a global statistical model from a multi-valued function. This function is generated by means of filter responses over the texture regions. Linear discriminant analysis is performed to obtain a statistical classifier embodied into the snake scheme. Given an input image composed by different texture types, a likelihood map is built and the discriminant snake deforms on it to delineate regions with similar texture descriptions according to the learned texture patterns. Our method is tested on two different image applications: aerial images and medical (ultrasound) images, and the results are very encouraging.

1. INTRODUCTION

Over the years, many approaches have been developed to reach the difficult goal of object segmentation. Deformable models [1] have proved their advantage with respect to other segmentation techniques due to their ability to incorporate high-level knowledge (assumptions for object contour smoothness and connectivity[1], approximate model[2, 3]) into the low-level image processing by snakes. The bulk of the existing work in segmentation using active contour models follows the two basic segmentation approaches: contour-based and region-based. Most deformable models (snakes[1], geodesic snakes [4], active shape models[2], Kalman snakes[5]) are edge-based; the snake is attracted by local image structures with high gradient response or high response of edge point detectors. While edge-based segmenting snakes are well explored [1, 4, 5], region-based snakes have been paid less attention. One of the most difficult problems in using deformable models is the choice of an external energy of the snake to select the image features relevant to the target object and the precise determination of the types of images for which it is efficient[6]. Real images are so different from each other that it is difficult to expect a unique algorithm to be able to segment all of them. To help to the snake segmentation *a priori* knowledge about the application problem must be introduced into the snake framework. In [7] deformable templates are presented as parametric shape models with relatively few degrees of freedom; prior knowledge on the object shape is used to design a prototype template that allows a restricted family of deformations to adjust to the image features. To free the user from the task of modeling, active shape models as statistic methods of building models by learning patterns of variability from a training set have been described [2, 8, 9, 10]. Active shape models are able to deform to fit data in ways consistent with the training set. In general, the statistic approach is a general framework to introduce different statistic information of the problem into the image processing technique. In [11] we have presented discriminant snakes based on statistic learning of image features of contour appearance and integrating it into the snake framework. In this paper we extend this contour-based approach to the problem of region-based segmentation. Recently, different region-based snake models have been proposed. In concrete applications it is possible to design the snake to classify image features assuming known parameters of the statistical laws [12]. More general approaches treat unknown statistics parameters of image regions. In [6] a probabilistic framework for region segmentation is given where different probability density functions from the exponential family are allowed. The parameters of the probability function are determined and dynamic programming techniques are applied to deform the snake to detect the image regions. In [13] a region-growing method by snakes is developed where the snake expands to group pixels with high rate of ”goodness”. The ”goodness” is expressed in terms of first order statistics like difference of pixel intensity and a seed mean intensity. The approach is extended to treat image texture where ”goodness” is expressed by the image texture energy using the Laws masks. A further development of region-based segmentation techniques by snakes is proposed in the region competition method [14] where three main segmentation approaches based on snakes, statistical region growing and Minimum Description Length segmentation methods are unified within the same framework. Within an iterative scheme derived from the variational principle on the snake energy minimization, the snake parameters and probability parameters are updated in a sequential way. The snake deforms so that the regions along the snake boundary are competing by comparing their mean and variance to the mean and variance of the seed regions, and assigned to either the interior or exterior regions. To segment texture regions the region competition is extended to compare first order statistics of the image gradient instead of the region intensity. In [15] a further development of region competition model has been proposed developing flows for segmenting trimodal and more general forms of multimodal imagery. Combining evolving curves and ternary flows, sub-regions of image areas can be identified as long as mean and variance as discriminating statistics are sufficient to distinguish various regions within a given image. In [16] a geodesic active contour for supervised texture segmentation is proposed where texture analysis/modeling is composed of two steps. A set of predefined Gabor filter operators is applied to a preferable texture pattern and to the input image. Then, each filter response is statistically modeled using a multi-component conditional probability density function. The segmentation is performed using a geodesic active contour model, where the boundary-based information is expressed via conditional probabilities. The defined objective function is minimized using a gradient-descent method, the obtained partial differential equation that deforms the initial curve towards the minimum is implemented using a level-set approach.

In contrast to the boundary-based approach presented in [16], our main goal is to obtain region segmentation by discriminant snakes. Our discriminant snakes, similarly to [16], rest on the fact that the mean and the variance of region grey-level are not sufficient to discriminate different texture regions. The feature space is generated by filtering the input and the preferable pattern image by a bank of filters composed by Gaussian derivatives of different scale and order to capture local image structure and scale of image features. This fact leads to a construction of high-dimensional image feature space. The novelty of the discriminant snakes for texture segmentation consists of applying linear discriminant analysis (LDA) to assure optimal texture discrimination. The snake deforms on a likelihood map expressed in terms of Mahalanobis distance to segment regions of pixels with high probability to possess the desired texture.

The remainder of the paper is organized as follows: section 2 explains the construction of the textured image feature space and its integration into the snake framework. Section 3 discusses our applications and results and the article finishes with conclusions.

2. TEXTURE SEGMENTATION BY DISCRIMINANT SNAKES

2.1. Building image feature space for texture description

The success of the segmentation of an object is based on the discrimination of locally computed image features and their spatial continuity. Obtaining correct result of the segmentation is intricately tied to the type of the sought features and the criteria used for discriminating between the extracted features [18]. The feature space must be capable of representing any image features of interest. As any image can be represented as a combination of its derivatives, we apply a convolution of the image by a bank of Gaussian derivative filters to extract the texture image features [19]. We have studied different techniques of texture analysis[17] (gray-level cooccurrence parameters, Laws masks, digital transform methods, etc.) and obtained that Gaussian derivatives of different scales and orders are optimal to detect texture regions by snakes. Our segmentation approach relies on derivative features computed over multiple spatial orientations and scales to capture texture features of different scale and structure. In particular, the bank of filters contains derivatives up to degree three (variance of higher-order filters are expected to approach that of image noise, and tend to be highly correlated to the outputs of lower order filters [19]).

As it is well known, the directional derivative operator is steerable, hence we use a set of basis filters $\left\{G^d(x,y,\sigma,\theta_k)\right\}_{k=1}^{d}$ for defining the derivative of Gaussian of degree d at arbitrary angle ϕ, $G^d(x,y,\sigma,\phi)$. Derivative of degree d at arbitrary angle can be obtained by the interpolation of $d+1$ equiangular orientations [20].
Given the basis functions for each filter degree, filters at arbitrary orientations can be synthesized by means of interpolant functions:

$$G^d(x,y,\sigma,\theta) = \sum_{i=1}^{d+1} G^d(x,y,\sigma,\frac{(i-1)\pi}{d+1})k_{id}(\theta),$$

where the interpolants $k_{id}(\theta)$ are function of the filter degree d [20]. We define $\mathcal{G}_{\mathcal{D}_\Sigma}$ as the filter bank with derivatives until $\mathcal{D}$ degree and N_Σ scales: $\sigma \in \{2^0, 2^1, \ldots, 2^{N_\Sigma - 1}\}$.

2.2. Multi-valued potential field and external force of the discriminant snakes

Given the responses of the different filters, a multivalued potential of the discriminant snakes is defined as follows:

$$\begin{array}{rcl} \mathcal{P}:\mathcal{I} & \longrightarrow & \mathbf{R}^{d_\mathcal{G}} \\ (i,j) & \longrightarrow & (p_1,\ldots,p_{d_\mathcal{G}}) \end{array}$$

Hence, the *potential* denotes the responses of filters and the *external energy* refers what each snaxel interprets on the multivalued potential (similarity and distance to target configurations).

On one hand, the relative importance of derivative features depends on the task domain. On the other hand, the human selection needs expert knowledge on image processing and it is prone to error. It seems natural to perform a self-training for reduction of the space and weighing the features. We apply a technique commonly used for dimensionality reduction based on Principal Component Analysis (PCA) [21].

Given the problem of segmentation, a set of N sample image feature vectors on object region and outside the object $\{s_1, s_2, \ldots, s_N\}$ are chosen, taking values in an $d_{\mathcal{G}}$-dimensional space, where $d_{\mathcal{G}}$ is the dimension of the bank of filters applied to the original image. Each component of vector s_i corresponds to a response of a filter (image convolution by a Gaussian derivative). Looking for a target texture k, each image feature s_j can be assigned to one of two classes $\{C_k, \bar{C}_k\}$, representing the pixels belonging to the region k and the complementary class (remainder scene). Our goal is to obtain an optimal linear transformation that maps the original $d_{\mathcal{G}}$-dimensional space into an 1-dimensional space where the classification of image features is applied by measuring the Mahalanobis distance to the class center of the corresponding learned configuration.

Linear discriminant functions are used to assign image feature filter responses to one of both populations (target region configuration versus non-target) by Fisher linear discriminant analysis (FLDA). After FLDA, each region has its own classifier $\mathcal{V}_{C_k}$ that defines the image features the snake is looking for. The scalar product of the mean feature vector μ_{C_k} of the region and the classifier vector gives the center of the class $\mathcal{O}_{C_k}$ of points in the feature space that corresponds to the region of interest:

$$\mathcal{V}_{C_k} = V_{k\_opt} \quad \mathcal{O}_{C_k} = \mathcal{V}_{C_k}^T \mu_{C_k}.$$

We define the local external energy of the snake by measuring the similarity of the actual image features $\mathcal{P}_f$ in the current location of the snake to the desired texture description in terms of the Mahalanobis distance from the projection of the image feature vectors $\mathcal{P}_f$ to the class center:

$$\begin{aligned} D_{C_k} &= \left(\mathcal{V}_{C_k}^T(\mathcal{P}_f - \mu_{C_k})\right)^T \left(\mathcal{V}_{C_k}^T(\mathcal{P}_f - \mu_{C_k})\right) \\ \mathcal{P}_f &= \mathcal{G}_{\mathcal{D}\Sigma} * \mathcal{I}, \end{aligned}$$

where $\mathcal{I}$ is the original image and $\mathcal{G}_{\mathcal{D}\Sigma}$ is the bank of filters. As a result, each target region generates its own distance map from the constant multivalued potential. The snake is located on the likelihood map and expands to detect regions of pixels with high likelihood to belong to the target texture. Fig.2 (c) illustrates the likelihood map generated from the image in Fig.2 (b), where bright pixel values correspond to high likelihood values of belonging to the interior of the vessel (upper region).

3. EXPERIMENTAL RESULTS AND DISCUSSION

The first application considers the process of alleviating the tasks of digitizing region contours, to obtain the vector representation of the regions boundary that appears in an aerial photograph. By the experience of many users/operators this is one of the most time consuming tasks related to the generation of Geographic Information System. The most common approach of agricultural field segmentation is focused on pixel classification and grouping (clustering). However, these local techniques do not have information about the image regions number and location, neither control the obtained boundary shape. This fact leads to generation of irregular boundaries, small holes and oversegmented image results. Discriminant snakes allow combining the advantages of region growing and snakes to divide the raster image into homogeneous texture parcels even in case of parcels with the same mean and variance (fig.1). Depending on image homogeneity after applying the texture analysis, we obtained correct classification of 87% of parcel pixels leaving small holes or irregularities on the region boundary. Applying the discriminant snake that combines image texture statistics and geometric constrains (smoothness, topology) allow to overcome the imperfection of the classification process.

The second application is related to analysis of intravascular ultrasound images (IVUS). IVUS provide a unique 2D *in vivo* vision of the internal vessel walls, determining the extension, distribution and treatment of the aterosclerotic, fibrotic plaques and thrombus, and their possible repercussion on the internal arterial lumen. The segmentation of IVUS is a difficult task even for medical experts due to the speckle appearance of ultrasound impedance in the image. Statistic methods combined with the snakes allow to easy and automate the process of vessel segmentation (fig.2).

4. CONCLUSIONS

In summary, we have presented discriminant snakes for texture segmentation integrating the three techniques: texture analysis, linear discriminant analysis and snakes as well as studying the optimal conditions of the integration approach: the optimal kind of image features for texture analysis as well as applying statistical analysis on image features based on FLDA.

5. REFERENCES

[1] M. Kass, A. Witkin, and D. Terzopolous, "Snakes: Active contour models," in *International Conference on Computer Vision, London*, 1987, pp. 259–268.

[2] 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, January 1995.

[3] P. Radeva, J. Serrat, and E. Martí, "A snake for model-based segmentation," in *Proceedings of the International Conference on Computer Vision - ICCV'95*, June 1995.

[4] V. Caselles, R. Kimmel, and G. Sapiro, “Geodesic active contours,” *International Journal of Computer Vision*, vol. 22, no. 1, pp. 61–79, 1997.

[5] A. Blake, R. Curwen, and A. Zisserman, “A framework for spatiotemporal control in the tracking of visual contours,” *International Journal of Computer Vision*, vol. 11, no. 2, pp. 127–145, 1993.

[6] Chesnaud Ch., Refregier Ph., and Boulet Vl., “Statistical region snake-based segmentation adapted to different physical noise models,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 21, no. 11, pp. 1145–1157, 1999.

[7] A. Yuille, C. Peterson, and K. Honda, “Deformable templates, robust statistics and hough transforms,” in *SPIE - Geometric Methods in Computer Vision*, July 1991, vol. 1570, pp. 166–174.

[8] Leventon M.E., Grimson W.E.L., and Faugeras O., “Statistical shape influence in geodesic active contours,” in *Proceedings of Computer Vision and Pattern Recognition*, 2000.

[9] Ch. Nastar and N. Ayache, “Frequency-based nonrigid motion analysis: Application to four dimensional medical images,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 18, no. 11, pp. 1067–1079, November 1996.

[10] Lanitis A., Taylor C. J., and Cootes T. F., “Automatic face identification system using flexible appearance models,” *Image and Vision Computing*, vol. 13, no. 5, pp. 393–401, 1995.

[11] Pardo X. and Radeva P., “Discriminant snakes for 3d reconstruction in medical images,” in *Proceedings of 15th International Conference on Pattern Recognition*, 2000, vol. 4, pp. 336–339.

[12] Reno A.L., Gillies D.F., and Booth D.M., “Deformable models for object recognition in aerial images,” in *Proceedings of the SPIE Conference Automatic Target Recognition VIII*, 1998, vol. 3371, pp. 323–333.

[13] Ivins J. and Porrill J., “Active region models for segmenting textures and colours,” *Image and Vision Computing*, vol. 13, no. 5, pp. 431–438, 1995.

[14] S. Ch. Zhu, T. S. Lee, and A. L. Yuille, “Region competition: Unifying snakes, region growing energy/Bayes/MDL for multi-band image segmentation,” in *Proceedings of the International Conference on Computer Vision - ICCV’95*, June 1995, pp. 416–423.

[15] Yezzi A., Tsai A., and Willsky A.S., “A statistical approach to snakes for bimodal and trimodal imagery,” in *Proceedings of 7th International Conference on Computer Vision*, 1999, vol. 1, pp. 898–903.

[16] Paragios N. and Deriche R., “Geodesic active contours for supervised texture segmentation,” in *Proceedings of 7th International Conference on Computer Vision*, 1999, vol. 1, pp. 926–932.

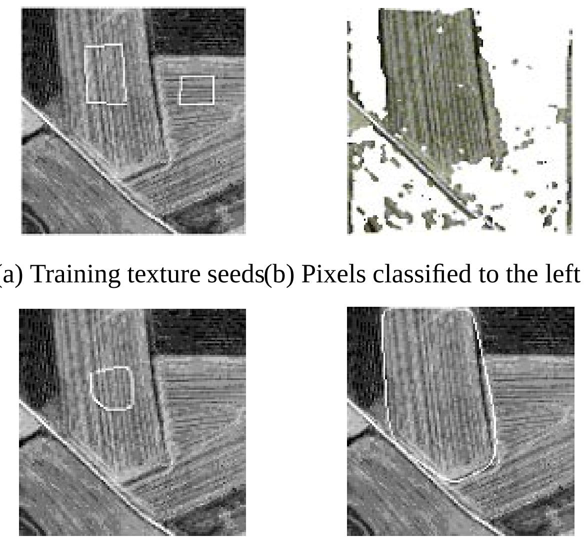
[17] Haralick R.M. and R. Bosley, “Texture features for image classification,” in *3rd ERTS Symp. NASA SP-351*, 1973, pp. 1219–28.

[18] Jain A.K., Ratha.N.K., and Lakshmanan S., “Object detection using Gabor filters,” *Pattern Recognition*, vol. 30, no. 2, pp. 295–309, 1995.

[19] Rao R.P.N. and Ballard D.H., “Natural basis functions and topographic memory for face recognition,” in *Proc. International Joint Conf. on Artificial Intelligence*, 1995, pp. 10–17.

[20] Freeman W.T. and Adelson E.H., “The design and use of steerable filters,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 13, no. 9, pp. 891–906, 1991.

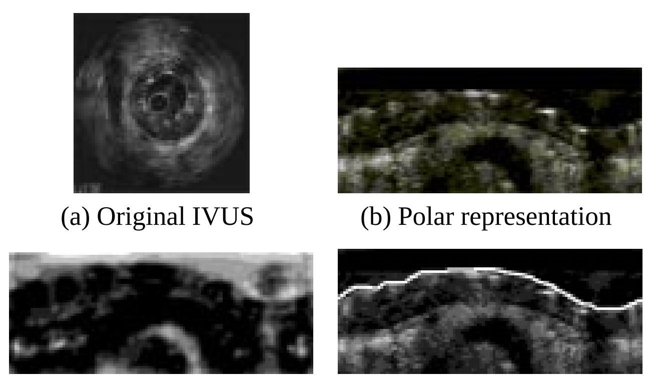
[21] Turk M. and Pentland A., “Eigenfaces for recognition,” *J. Cognitive Neuroscience*, vol. 3, no. 1, 1991.



(a) Training texture seeds (b) Pixels classified to the left parcel

(c) Initial snake (d) Final result

Fig. 1. Discriminant snakes segmenting agricultural fields.



(a) Original IVUS (b) Polar representation

(c) Likelihood map (d) Segmentation of the vessel wall

Fig. 2. Example of detecting vessel wall in IVUS.