SHAPE AND APPEARANCE MODELING WITH FEATURE DISTRIBUTIONS FOR IMAGE SEGMENTATION

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ABSTRACT

This paper presents a new approach to prior shape and appearance modeling for use in curve evolution-based segmentation. The new method is based on the unified use of feature distributions and allows the incorporation of coupled prior information about shape and appearance into the curve evolution segmentation process. Examples show the accurate placement of boundaries in challenging situations; for example, in cases where an intensity boundary does not exist.

1. INTRODUCTION

Segmentation is an important task in many domains of medical imaging. Curve evolution methods have become a popular approach to segmentation because they allow explicit representation of boundary location, convenient handling of object topology, efficient implementation, and possess variational and associated probabilistic interpretations. Inclusion of prior shape and appearance information in the curve evolution process can greatly improve the final result. This paper presents novel prior models for curve-evolution-based segmentation methods.

In a typical curve evolution scheme the shape-capturing curve is evolved under the combined action of two classes of forces: those dependent on the observed image data (data-dependent forces) and those reflecting prior knowledge about the segmented shape or boundary (regularizing forces). The simplest data dependent force positions the boundary to maximize the image gradient magnitude there. Alternatively, the popular Chan and Vese model [1] attempts to maximize the uniformity of intensities in the different regions created by the boundary. Other models [2], attempt to maximize the uniformity of certain higher order statistics of the intensities in each region. These methods are insensitive to variations of intensity along the boundary and seek a certain intensity homogeneity. Existing prior shape forces are even more simple. Typically, only curve length is penalized, leading to smoother boundaries.

Attempts have been made to develop more complex forces capturing prior information. For example, the probabilistic appearance model in [3] links appearance to the boundary through the distance function, but this model drives the boundary towards a most likely intensity and curvature through a MAP formulation. While not strictly a curve evolution method, the Active Appearance Model (AAM) in [4] creates detailed intensity and shape models sensitive to boundary position. However, the AAM approach enforces similarity over the entire model domain, requires identification of reliable boundary landmarks in each image (effectively doing registration), and is based on PCA of observed pixel values and boundary control points, resulting in generalization sensitivity.

In contrast, our proposed approach to prior construction is based on the concept of shape distributions [5], which we use to encode both prior shape information as well as appearance information. Previously we have developed purely shape-based priors [6] and in this paper we extend those results to include coupled shape and intensity priors. Our approach is based on matching distributions of shape and intensity features of a target shape rather than driving the shape towards a given set of mean values or seeking maximal homogeneity of intensity or shape characteristics. Since our model is based on the distribution of intensity, edges are not even needed to define boundary location, which is useful in certain medical segmentation contexts. Through careful feature choice, our model can be inherently insensitive to many geometric transformations (scaling, rotation, etc).

In the Sec. 2 we review the concept of shape distributions and its application to model shapes. In Sec. 3 we extend the shape distribution concept to joint appearance and shape modeling. In Sec. 4 we show the preliminary results obtained for synthetic and real segmentation problem, and Sec. 5 concludes the paper.

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2. SHAPE DISTRIBUTION PRINCIPLES

Shape distributions provide a powerful method of modeling shapes through distributions of features (e.g. curvature) derived from the boundary [5]. Some feature localization information is lost while information on feature existence and frequency is preserved. This averaging appears to provide robust generalization properties, and the method has been successfully applied to recognition tasks.

We now review our method of shape prior construction based on shape distributions (see [6]). Let $\Phi \in \Omega$ be a continuously defined boundary feature (e.g. curvature), and let λ be a variable spanning the range of values Λ of the feature. Let $H(\lambda)$ be the cumulative distribution function (CDF) of Φ:

$$H(\lambda) = \frac{\int_\Omega h\left\{\Phi(\Omega) < \lambda\right\} d\omega}{\int_\Omega d\omega} \quad (1)$$

where $h(x)$ is the indicator function, which is 1 when the condition is satisfied and 0 otherwise.

We define the prior energy $E_{\rm shape}(C)$ for curve C as:

$$E_{\rm shape}(C) = \sum_{i=1}^{M} w_i \int\limits_{\Lambda} \left[\overline{H}_i^{\rm shape}(\lambda) - H_i^{\rm shape}(C,\lambda)\right]^2 d\lambda \quad (2)$$

where M is the number of different shape distributions (i.e. feature classes) being used to represent the object, $H_i^{\rm shape}(C,\lambda)$ is the distribution function of the i^{th} shape feature class, and the non-negative scalar weights w_i balance the relative contribution of the different feature distributions. Prior knowledge of object shape behavior is captured in the set of target distributions $\overline{H}_i^{\rm shape}(\lambda)$. These target distributions $\overline{H}_i^{\rm shape}(\lambda)$ can correspond to a single prior shape, an average derived from a group of training shapes, or can be specified by prior knowledge (e.g. the analytic form for a primitive, such as a square).

We use two specific (discretized) shape feature classes in our experiments in this work:

- **Feature class # 1.** Inter-curve Distances
  The set of feature values consist of samples of the normalized distances between points on the curve.

$$\{F\} = \frac{\{d_{ij} \;\mid (i,j) \in S\}}{\text{mean}\left(\{d_{ij} \;\mid (i,j) \in S\}\right)} \quad (3)$$

  The set S defines the combinations of discrete points on the curve being used. The feature defined is invariant to shape translation, rotation and scale.

- **Feature class # 2.** Multiscale curvature.
  The set of feature values consist of samples of angles between points on the curve.

$$\{F\} = \{\angle_{i-j,i,i+j} \quad (i,j) \in S\} \quad (4)$$

  where $\angle(ijk)$ is the angle between points i, j, and k on the curve. Again, the set S defines the combinations of discrete points on the curve begin used.

3. EXTENSION TO COMBINED INTENSITY AND SHAPE PRIORS

Now we describe our extension to include prior appearance information. In our approach, we compute the distributions of intensity-based features measured parallel to the boundary of the shape. We then seek a solution whose distribution matches this prior such distribution, rather than a solution whose intensities maximize the distribution. This approach does not require uniformity of region intensity properties and appears to have good generalization properties. To find a solution the dissimilarity of observed and prior intensity distributions are used to create a curve evolution force via a variational approach.

To generate our appearance model, an orthogonal coordinate system aligned with the tangent and normals to the boundary is constructed and image intensity values in a rectangular patch are measured, as illustrated in Fig. 1. Let O

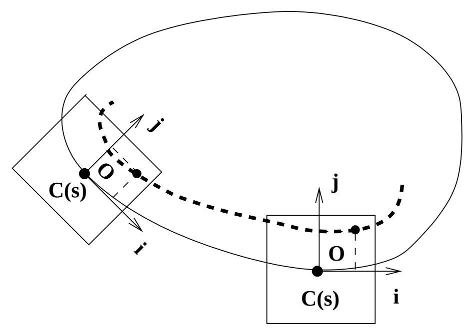

Fig. 1. Image patch based feature values measured along the boundary. Point O (patch coordinate system origin) is positioned at $C(s)$ (current boundary point). j-axis is aligned with local inward normal. Two instances are shown.

be the origin of this coordinate system at a given point on the boundary and x_{ij} be a sample point with coordinates i and j. We choose the a set of such points $S = \{x^1, x^2, ...x^m\}$ in this boundary based coordinate system. There is no restriction on this set of points, but currently we make the set symmetric with respect to the j-axis and to include O in the set. Each point $x^k = (i^k, j^k)$ in S gives rise to an intensity function corresponding to the trajectory of the point x^k as the coordinate origin is moved around the boundary. A typical such trajectory is shown as the dotted line in Fig 1. Let $\Phi^k(s)$ be an associated feature function that is computed from this intensity function for the k-th point trajectory, where s is arclength around the boundary. The simplest approach, and what we have done to date, is to simply use the intensity values along the trajectory themselves, so the k-th intensity feature is given by:

$$\Phi^k(s) = I(x^k, s) = I\left(C(s) + \mathbf{R}\left(s, \mathbf{n}(s)\right)[i^k \;\; j^k]^T\right) \quad (5)$$

where I is the image, C is the boundary parameterized by arc length s, $n(s)$ is the local normal and $\mathbf{R}(s, \mathbf{n}(s))$ is the 2D rotation matrix aligning $\mathbf{n}(s)$ with j-axis of the patch coordinate system. Similar to our distribution-based shape model, we then generate the CDF of each such intensity feature $H_k^{\text{int}}(C, \lambda)$, following (1). The collection of these m distributions is the basis of our intensity appearance model.

We combine this intensity or appearance model with the shape term in (2) to define an overall intensity and shape prior curve energy:

$$E = \sum_{k:x^k \in S} \int \left[\overline{H}_k^{\text{int}}(\lambda) - H_k^{\text{int}}(C, \lambda)\right]^2 d\lambda + E_{\text{shape}} \quad (6)$$

where E_{shape} is given in (2) and includes only shape terms.

We aim to drive the curve C to minimize this energy by finding an appropriate curve flow through variational principles. The curve flow at location s minimizing (6) is given by

$$\nabla E(C)(s) = \nabla E_{shape}(C)(s) + \quad (7)$$
$$\sum_{k:x^k \in S} \mathbf{n}(s) \cdot \nabla I(x^k, s)\left[H_k^*(I(x^k, s)) - H_k(I(x^k, s))\right]$$

where $\nabla E_{shape}(C)(s)$ is computed according to [6] and $I(x^k, s)$ is defined in (5).

4. RESULTS

Our approach is designed to model directly the intensity distributions around the boundary of the object of interest. It makes no explicit assumption about the presence of edges and/or image gradients nor does it enforce uniformity of region statistics. Therefore, we expect our approach to show the greatest advantage over traditional approaches when modeling objects without prominent edges and with uniform region statistics inside and outside the region of interest. These represent some of the most difficult segmentation cases. Region and gradient-based segmentation methods will not work on such a problem.

In our first example we construct such a synthetic segmentation problem without a gradient-based boundary and with matching first and second order statistics in the interior and exterior regions. In Fig. 2 we show the observed image with the desired true boundary indicated by a solid black line. By construction, the intensity gradient is uniform across the image except for the two diagonals. Therefore, any segmentation method that relies on gradient information to localize boundary will have difficulty on this image. In addition, the mean intensity and variance of the intensity inside and outside of the object boundary are the same, causing problems for typical region based methods. Furthermore, the distributions of intensity perpendicular to the boundary on this image are uniform, so local intensity-based methods will also not work.

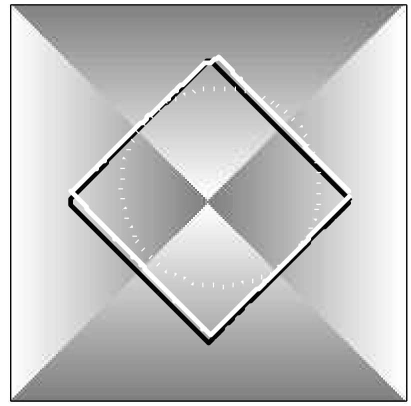

Fig. 2. Example 1. Segmentation with shape/intensity distribution prior and shape distribution prior. True shape - solid black line; Initial contour - dashed line; Final segmentation contour - solid white line.

To apply our method we use an intensity appearance model constructed using only 5 points for the set S sampled along the trajectory of the actual object boundary. The coordinates (i,j) of the points in the boundary coordinate system are (-10,0), (-5,0), (0,0), (5,0) and (10,0). For the prior shape model E_{shape} we use the prior shape distribution in (2) with the two feature classes in Sec. 2. The prior distributions $\overline{H}_i^{\text{shape}}(\lambda)$ were computed using the true boundary. The solid white line in Fig. 2 shows the corresponding segmentation result. The segmenting contour matches the true contour quite well. This example shows the potential effectiveness of our prior on a segmentation problem where intensity is constant along the intended boundary and the intended boundary is not supported by edges.

In our second example, we segment the lenticular nucleus structure in an axial slice of a brain MRI. Segmentations of the lenticular nucleus structure by experts often include subregions with different average intensity and typically does not follow the strongest perceivable edge everywhere. For example, in Fig. 3 we show a lenticular nucleus from our data set that has been segmented by an expert. Inside the object, one can distinguish areas with significantly different intensity and the expert segmented boundary is not aligned with the strongest gradient everywhere.

We desire a segmentation that is as close as possible to the expert segmentation. For our approach, we construct both our prior appearance and shape models based on 10 training images containing expert segmented shapes. The intensity model is again based on the 5 sample points described above. The prior shape model (2) is again based on the two feature

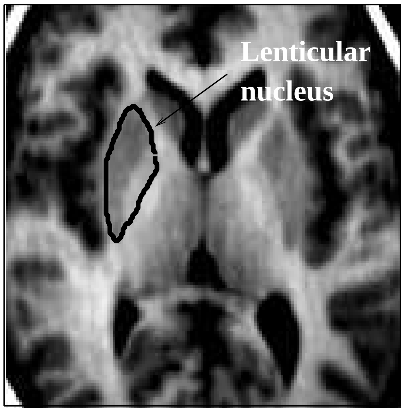

Fig. 3. Expert segmented left lenticular nucleus showing variation in intensity within the structure and lack of a consistent gradient along the boundary.

classes in Sec. 2. Both the prior shape and intensity distributions $\overline{H}_i^{\text{shape}}(\lambda)$ and $\overline{H}_i^{\text{int}}(\lambda)$ and obtained by averaging the distributions of the 10 samples in the training set. To test the model, the segmentation is performed on an image that is not included into the training set. In Fig. 4 (a), we show the segmentation result. For comparison, in Fig. 4 (b) we show the segmentation result obtained using the approach in [2] for intensity term combined with same shape prior given by eq. 2, which demonstrates that in this medical example homogeneity of region properties is not a good metric for segmentation.

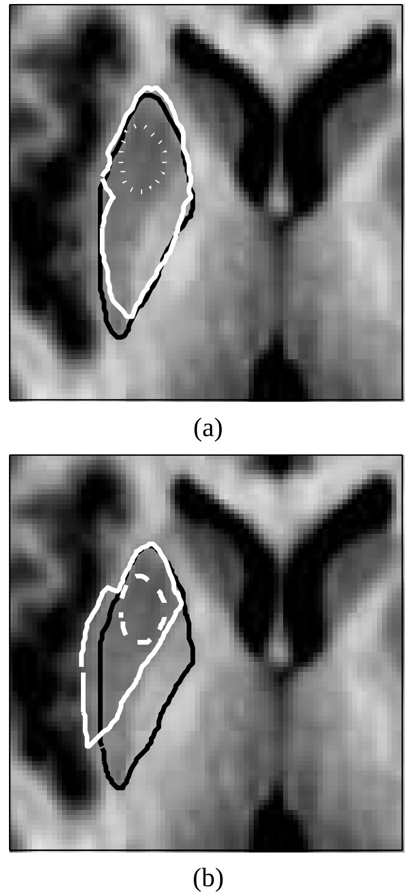

Fig. 4. Example 2. (a) Segmentation with shape/intensity distribution prior. (b) Segmentation with only shape prior and intensity model in [2]. True shape - black solid line; Initial contour - dashed line; Final segmentation contour - solid line.

5. CONCLUSIONS

We present preliminary results on a unified approach to appearance and shape modeling. The method is based on concept of shape distributions and allows the capture of salient shape and appearance properties in images. The method can work where current popular approaches, based on maximizing uniformity of region properties or seeking maximal gradient magnitude, do not. Many challenging medical segmentation problem possess such properties. The concept of feature distribution-based appearance models can be easily extended to 3D, which is the topic of our current research.

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