REGION-BASED IMAGE SEGMENTATION USING TEXTURE STATISTICS AND LEVEL-SET METHODS

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ABSTRACT

We propose a novel multi-class method for texture segmentation. The segmentation issue is stated as the minimization of a region-based functional that involves a weighted Kullback-Leibler measure between distributions of local texture features and a regularization term that imposes smoothness and regularity of region boundaries. The proposed approach is implemented using level-set methods, and partial differential equations (PDE) are expressed using shape derivative tools introduced in [12].

As an application, we have tested the method using co-occurrence distributions to segment synthetic mosaics of textures from the Brodatz album, as well as real textured sonar images. These results prove the relevance of the proposed approach for supervised and unsupervised texture segmentation.

1. INTRODUCTION

Texture segmentation has long been an important topic in image processing. It aims at segmenting a textured image into several regions with the same texture features. An effective and efficient texture segmentation method will be very useful in applications like the analysis of aerial, biomedical and seismic images as well as the automation of industrial applications.

Recently, features computed as statistics of local filter responses have been largely used in texture analysis and several studies have shown the relevance of marginals of a large set of filters to characterize textures. Zhu et al.[2] proposed a maximum entropy theory for learning probabilistic texture models from a set of empirical distribution of filter responses. Gimel'farb used the difference co-occurrence statistics to model texture [6] and later, Xiuwen Liu et al.[3] proposed a local spectral histogram, defined as the marginal distributions of feature statistics for texture classification.

Image segmentation is also an active field of research. Pixel-based and region-based techniques can be seen as the two major categories of approaches. Whereas pixel-based schemes, such as standard Markov random fields, consider image segmentation as a labeling issue at the pixel level, region-based approaches directly search for a relevant image partition. In this second category, we can cite active contours or deformable models [1, 9, 7]. As far as texture segmentation is concerned, region-based techniques appear more adapted, since the texture characteristics are defined at the region level. Indeed, pixel-based texture segmentation generally relies on the use of local texture features computed within a predefined window around each pixel. Hence, texture features extracted for pixels close to region boundaries involve a mixture of texture characteristics, which may lead to a lack of accuracy in localizing the boundaries of the texture region. In contrast, region-based approaches, especially active contours associated with a level-set setting, offers an efficient manner to cope with texture and geometrical features at the region level.

In this work, we aim to combine the use of statistical distributions of filter responses for texture characterization and region-based image segmentation within a level set framework. The proposed approach relies on a texture-based similarity measure defined as a weighted Kullback-Leibler measure between distributions of texture filter responses computed inside regions and on regularity constraints set to region boundaries. This work can be viewed as an extension of the approach presented in [12], where the distributions of local features (namely, gray-level histograms) were also used to characterize each region. The main contributions of this paper are the application to texture segmentation and the treatment of supervised and unsupervised multi-class issues.

The presented paper is organized as follows. In Section 2, texture characterization and modeling are described. Section 3 briefly reviews active contour methods and the level set approach. In Section 4, the energy functional and its derivation are presented and the curve evolution equations are computed. Section 5 presents the generalization of the proposed approach to the unsupervised case and in Section 6 various results are shown on synthetic images containing textures from the Brodatz album and on natural sonar images.

2. TEXTURE DESCRIPTION

Features computed as statistics of local filter responses are widely used for texture analysis and segmentation. Many statistical and filtering approaches have been compared [4]. Among the most effective features are co-occurrence matrices, wavelet frames, quadrature mirror filter-banks (QMF)

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and Gabor filters. It should be noted that none of these feature classes outperforms the others for all textures.

Here, we will not address the problem of feature selection, but we choose a set of different filters computed for different parameters. Let $h_j, j = 1 : J$ be the image of filter responses to the j^{th} filter taking its values in R_j. R_j is a set of $\Re^m$, m is the filter output value dimension and let $P_j, j = 1 : J$, be their respective distributions. Using Parzen window estimation, $P_j(\alpha)$ $\alpha \in R_j$ for the j^{th} distribution is computed on a domain Ω as:

$$P_j\left(\alpha, \Omega\right) = \frac{1}{|\Omega|} \int_{\Omega} g_{\sigma_j}\left(h_j(x) - \alpha\right) dx. \tag{1}$$

where g_{σ_j} is a Gaussian kernel of mean 0 and variance σ_j.

To compare feature histograms, we use the Kullback-Leibler divergence which is a relevant similarity measure between distributions. The Kullback Leibler distance (KL) between two distributions P and Q, is defined as:

$$KL(Q, P) = \int Q(x) log\left(\frac{Q(x)}{P(x)}\right) dx \tag{2}$$

For two distribution sets $P = \{P_j\}_{j=1:J}$ and $Q = \{Q_j\}_{j=1:J}$, we define their dissimilarity measure as follows:

$$KL_w(Q, P) = \sum_{j=1}^{J} w_j^2 KL(Q_j, P_j) \tag{3}$$

where $\{w_j\}_{j=1:J}$ are weights such that $\sum_{j=1}^{J} w_j^2 = 1$. The weights can be computed according to the discrimination powers of the associated features (for instance, Fisher scores [11]).

3. ACTIVE CONTOURS AND LEVEL SET IMPLEMENTATION

The idea behind active contour segmentation methods is to evolve a parametric curve $C(s, t)$ in the image domain Ω. s may be its arc-length and t is an evolution parameter. The curve evolution is described by a partial differential equation (PDE) that drives the active contour to a minimum of a functional. The PDE is generally derived from an energy criterion as follows:

$$\frac{\partial C(s,t)}{\partial t} = FN \tag{4}$$

with $C(s, 0) = C_0$ an initial curve defined by the user. F is the velocity vector and N is the inward normal of C.

The parametric representation of the curve $C(s, t)$ is unsuitable for many applications since it does not allow for automatic change of topology, such as merging and breaking. Level set methods, introduced in Osher and Sethian [10] to track moving interfaces in the community of fluid dynamics, circumvent these topological problems. The key idea of level set methods is to represent the evolving curve $\Gamma = \partial\Omega$ with an implicit Lipschitz function φ which is defined by:

$$\begin{cases} \varphi(x, t) > 0 \text{ if } x \in \Omega \\ \varphi(x, t) = 0 \text{ if } x \in \Gamma \\ \varphi(x, t) < 0 \text{ otherwise} \end{cases} \tag{5}$$

The region Ω is entirely described by the level sets ($\varphi > 0$) and its geometrical quantities can be expressed by φ.

Evolving the curve C in its normal direction with speed F amounts to solving the differential equation [10]:

$$\frac{\partial \varphi}{\partial t} = |\nabla\varphi| F, \varphi(0, x, y) = \varphi_0(x, y) \tag{6}$$

where φ_0 is the initial contour.

4. SUPERVISED TEXTURE SEGMENTATION

Given a set of K texture models, we aim to determine the partition of the image into homogeneous regions according to texture characteristics. We assume that each texture $T_k, k = 1 : K$ is characterized by a set Q^k of its filter response distributions.

The segmentation issue is stated as the minimization of an energy criterion $E = E^1 + E^2 + E^3$, where E^1 is a texture-based data-driven term, E^2 a regularization term and E^3 a term needed to cope with multi-class segmentation.

4.1. Functional terms

E^1 is evaluated as the log-likelihood of a given partition with respect to texture models:

$$E^1 = \sum_{i=1}^{K} |\Omega_i| \, KL_w(Q^i, P(\Omega_i)). \tag{7}$$

where $P(\Omega_i)$ is a set of filter response histograms estimated inside the region Ω_i.

E^2 penalizes the region contour lengths and is expressed by:

$$E^2 = \sum_{i=1}^{K} \gamma_i \left|\partial\Omega_i\right|, \gamma_i \in \Re. \tag{8}$$

Using level set functions and regularized Heaviside and delta functions, E^2 can be written as follows (see [7] for details):

$$E^2 = \sum_{i=1}^{K} \gamma_i \int_{\Omega} \delta_\alpha(\varphi_i) \left|\nabla\varphi_i\right| dx. \tag{9}$$

H_α and δ_α are Heaviside and delta functions respectively, so that: when $\alpha \to 0$, $H_\alpha \to H$ and $\delta_\alpha \to \delta$, and $H_\alpha^{'} = \delta_\alpha$ (in the sense of distributions).

$$H_\alpha(x) = \begin{cases} \frac{1}{2}\left(1 + \frac{x}{\alpha} + \frac{1}{\pi} sin\left(\frac{\pi x}{\alpha}\right)\right) \text{ if } |x| \leq \alpha \\ 1 \text{ if } x > \alpha \\ 0 \text{ if } x < -\alpha \end{cases} \tag{10}$$

$$\delta_\alpha(x) = \begin{cases} \frac{1}{2\alpha}\left(1 + cos\left(\frac{\pi x}{\alpha}\right)\right) \text{ if } |x| \leq \alpha \\ 0 \text{ if } |x| < \alpha \end{cases} \tag{11}$$

E^3 is an additional term, required to cope with multi-class segmentation in order to fulfill the image partition condition. In the literature, there are several techniques for dealing with the representation of the different classes and their boundaries by level-sets [8, 9]. Our multi class model is inspired by the work of C. Zhao et al.[8]. The idea is to associate a level-set function $\varphi_k, k = 1, ..., K$ to each region Ω_k and the image partition condition is expressed by the following term:

$$E^3 = \frac{\lambda}{2} \int_\Omega \left(\sum_{k=1}^{K} H_\alpha(\varphi_k) - 1 \right)^2 dx \tag{12}$$

4.2. Computation of the evolution equation

The evolution equation of $\varphi_k, k = 1, ..., K$ related to the global functional E is given by:

$$\frac{\partial \varphi_k}{\partial t} = \partial\, E^1 + \partial\, E^2 + \partial\, E^3 \tag{13}$$

$\partial\, E^i, i = 1, 2, 3$ is the evolution equation term related to the functional term $E^i, i = 1, 2, 3$.

$\partial\, E^i, i = 2, 3$ are directly estimated from level set functions [1, 7].

$$\partial\, E^2(\varphi_k) = \gamma_k \delta_\alpha(\varphi_k)\, div\left(\frac{\nabla\varphi_k}{|\nabla\varphi_k|}\right). \tag{14}$$

$$\partial\, E^3(\varphi_k) = -\delta_\alpha(\varphi_k)\, \lambda \left(\sum_{i=1}^{K} (H_\alpha(\varphi_i) - 1) \right) \tag{15}$$

The evolution equation related to E^1 is more complex, since it involves computations over the spatial support of each region. To differentiate E^1, we use shape derivative tools, especially the Gâteaux derivative theorem given in [12]. The Gâteaux derivative of E^1 in the direction V is given by the following equation:

$$\begin{aligned} \left\langle E^{1'}(\Omega_i), V \right\rangle &= -\int_{\partial\Omega_i} KL_w\left(Q^i, P(\Omega_i)\right) \\ &+ \sum_{j=1}^{J} w_j^2 \left(1 - \int_{R_j} \frac{Q_j^i(\alpha)}{P_j(\alpha, \Omega_i)} g_\sigma(h_j(x) - \alpha) d\alpha\right)(V.N) da(x) \end{aligned} \tag{16}$$

where N is the unit inward normal to $\partial\Omega_i$ and da its area element. $\partial\, E^1$ is then given by:

$$\begin{aligned} \partial\, E^1(\varphi_k) &= \delta_\alpha(\varphi_k)(-KL_w(Q^k, P(\Omega_k)) \\ &\underbrace{- \sum_{j=1}^{J} w_j^2 \left(1 - \int_{R_j} \frac{Q_j^k(\alpha)}{P_j(\alpha, \Omega_k)} g_\sigma(h_j(x) - \alpha) d\alpha\right))}_{additional\ term} \end{aligned} \tag{17}$$

From this expression, we can notice the appearance of an additional term, which is the only one that depends locally on the value of the filter response at the pixel level. In fact, for small values of $\sigma_j, j = 1 : J$, the additional term resorts to:

$$-\delta_\alpha(\varphi_k) \sum_{j=1}^{J} w_j^2 \left(1 - \frac{Q_j^i(h_j(x))}{P_j(h_j(x), \Omega_k)}\right) \tag{18}$$

So, considering a given filter response h_j, if $\frac{Q_j^k(h_j(x))}{P_j(h_j(x), \Omega_k)} < 1$, (i.e., if more pixels with response value equal to $h_j(x)$ are inside the region Ω_k than in the reference class T_k), the additional term related to h_j is negative and according to the evolution equation (Eq.13), this leads to a decrease of $\varphi_k(x)$ and consequently the rejection of the pixel x from region Ω_k.

5. UNSUPERVISED SEGMENTATION

The method can be generalized to the unsupervised case. Initial level-sets are given by a k-means segmentation based on the texture model and the dissimilarity measure introduced in the previous sections. The unsupervised segmentation then alternates between estimating texture models $\{Q_j^k\}$:

$$Q_j^k(\beta) = \int_\Omega H_\alpha(\varphi_k) g_\sigma(h_j(x) - \beta) dx, \beta \in R_j. \tag{19}$$

and updating the segmentation partition according to Eq.13.

6. EXPERIMENTAL RESULTS

We experiment the proposed segmentation method using as filter response histograms, a set of co-occurrence distributions [5] computed for a displacement of one pixel in the four main directions $(0°, 45°, 90°, -45°)$. The additional term for this feature set is expressed as follows:

$$-\sum_{j=1}^{4} w_j^2 \left(1 - \int_{[1,N_g]^2} \frac{Q_j^k(\alpha, \beta)}{P_j(\alpha, \beta, \Omega_k)} g_\sigma(I(x) - \alpha) g_\sigma(I(x_j) - \beta) d\alpha d\beta\right), \tag{20}$$

where x_j is the translate of x according to the j^{th} direction, Ng is the number of gray-levels. Here we quantize the image with the k-means algorithm to $Ng = 10$ and we set $w_j = 1, \forall j$.

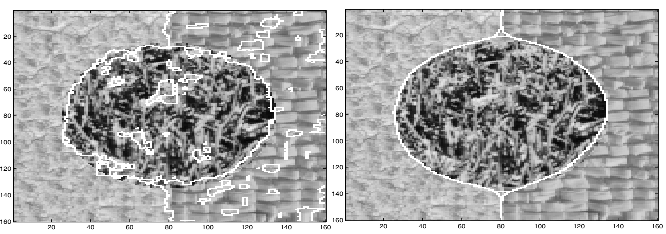
As most common methods, level-set functions are chosen to be the signed Euclidean distance to their zero level-sets. They are updated using gradient minimization techniques and re-initialized using a PDE based approach [7].

We initialize φ_k according to an initial moving-window segmentation. Given the set of co-occurrence distributions $P(x)$ estimated on an image window centered at x, pixel x is initially classified according to the following decision rule:

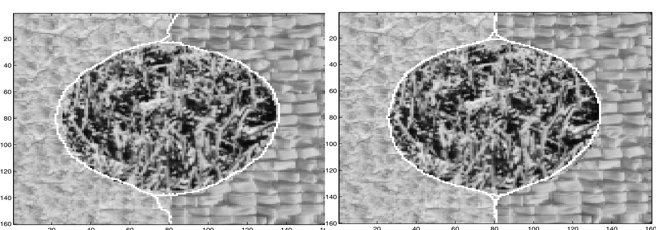
$$label(x) = \arg\min_k KL_w(Q^k, P(x)) \tag{21}$$

where KL_w is the weighted KL distance between co-occurrence distributions $P(x)$ at site x and texture models $\{Q_k\}$ (Eq.3).

Figure 1 presents the segmentation of a synthetic mosaic with 3 textures selected from the Brodatz database. This example shows the effectiveness of the method and its superiority to moving-window based segmentation. Final segmentations illustrate the robustness of the method to the initialization and highlight the gain provided by the proposed region-based approach compared to pixel-level labeling techniques, which rely on scale or window parameters to compute local texture features. Results coming from such techniques greatly depend on the choice of the scale or window parameter. In fact, great values of this scale parameter produce better estimates of the texture boundaries. However, they can also lead to the undesirable situation of multiple texture classes within a common window. In contrast, low values are less likely to contain multiple classes. However, the limited coverage may produce misleading features. The proposed region-based approach intrinsically circumvents these issues since the proposed energy criterion aims at forming homogeneous texture regions with smooth boundaries.



(a) Initialization 10x10 window (b) Final segmentation



(a) Initialization 40x40 window (b) Final segmentation

Fig. 1. Segmentation with an initialization with moving-window based segmentation using small and large windows

Figure 2 presents segmentation maps for a synthetic mosaic with 6 textures selected from the Brodatz database and for a real sidescan sonar image. The sonar image is composed of three textures: mud, sand and sand ripples. Let us stress that sand and ripple textures are partially mixed in the latter example. In both cases, we successfully recover the boundaries of the texture regions. In particular, in the second example, we retrieve relevant boundaries between the sand and ripple regions.

Figure 3 refers to examples of unsupervised classification for a 5-class Brodatz synthetic image (on the left) and a real sonar textured image (on the right). As in the supervised case, we accurately recover the region boundaries as well as the associated texture models.

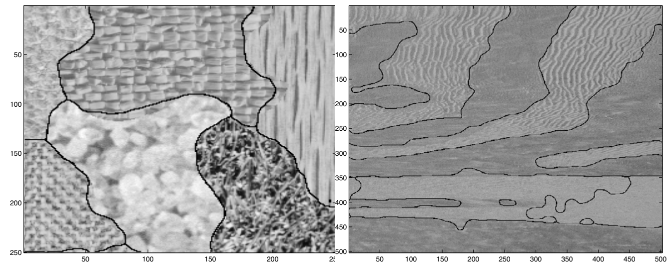


Fig. 2. Supervised segmentation.

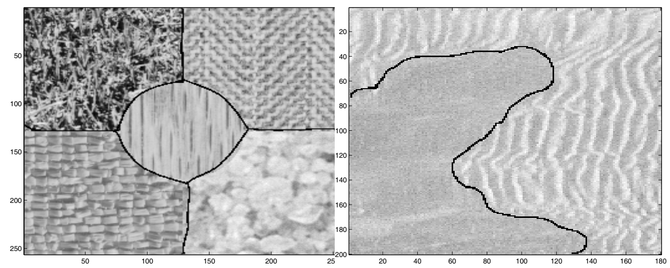


Fig. 3. Unsupervised segmentation.

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