Texture Segmentation by Grouping Ellipse Ensembles via Active Contours

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Texture plays an important role in human visual perception and offers crucial cues for solving a wide range of computer vision problems, such as image segmentation or scene analysis. The segmentation of texture is a key problem in computer vision and image understanding, the objective of which is to partition an image into several regions characterized by homogeneous texture attributes. Over the course of the past 40 years, numerous studies have been performed for texture segmentation, see [2, 3, 9, 10, 13, 14]. In this paper, we address the issue of structured texture segmentation, starting with the assumption that textures are statistical ensembles of local image structures, also known as *textons* [9, 16].

The study presented in this paper is inspired by works in mathematic morphology, more precisely, by *granulometry* [11, 12], which characterize textures relying on responses to morphological filtering with *user-specified structuring elements* of increasing size. The segmentation of synthetic and simple textural images can be achieved by partitioning the image according to some statistics of the granulometry [4, 5, 11], but it fails at describing complicated and highly structured textures [5]. Instead of using structuring elements and improving the discriminative powerful, alternative approaches have been proposed to analyze textures based on connected operators which perform directly on the level lines of images, see [6, 7, 15]. The main motivation of this paper is to investigate the granulometry-like approach in the context of texture segmentation.

Along the line of textons, we first suggest to represent textures by a tree of ellipses, which are derived from the level lines of images and can be regarded as explicit textons. As we shall see, the tree of ellipses of an image can be computed rapidly and efficiently, thus the proposed approach can overcome difficulties in the detection of texture primitives or texture elements as encontered in [1, 13]. Based on this representation, textures are subsequently characterized by geometric properties of and by relationships between these ellipses.

Thus, the modeling of a texture u is reduced to the modeling of the tree of ellipses $(\mathcal{E},\mathcal{T})$, as

$$p(u) = p(\mathcal{S},\mathcal{T}) \approx p(\mathcal{E},\mathcal{T}) \tag{1}$$

where $\mathcal{S} := \{s_i\}_{i=1}^N$ is the set of shapes, $\mathcal{E} := \{e_i\}_{i=1}^N$ is the set of ellipses and $\mathcal{T} : \mathcal{E}\times\mathcal{E}$ is the tree structure describing the relationships between ellipses. In our case, we use following attributes to describe each ellipse e:

$$(\alpha,\varepsilon,\kappa,\theta) := \Big(\log\sqrt{4\pi\lambda_1\lambda_2},\ \ \frac{\lambda_2}{\lambda_1},\ \ \frac{4\pi\sqrt{\lambda_1\lambda_2}}{\mu_{00}},\ \ \frac{1}{2}\arctan\frac{2\mu_{11}}{\mu_{20}-\mu_{02}}\Big) \tag{2}$$

where α, ε, κ and θ are respectively defined as log-size, elongation, compactness and orientation of the ellipses, μ_{pq} is the $(p+q)$-order moment and λ_1 and λ_2 (with $\lambda_1 \geq \lambda_2$) are the two eigenvalues of the inertia matrix of the corresponding shape s.

Texture segmentation is performed by grouping these properties in a unsupervised way. Specifically, the grouping step benefits from an active contour model based on Kullback-Leibler (KL)-divergence similar to the one of [8],

$$KL\big(p_{in}(f,C)\|p_{out}(f,C)\big) = \int_{-\infty}^{\infty}\Big(p_{in}(f,C)\cdot\frac{p_{in}(f,C)}{p_{out}(f,C)} \tag{3}$$

$$+\,p_{out}(f,C)\cdot\frac{p_{out}(f,C)}{p_{in}(f,C)}\Big)df. \tag{4}$$

The segmentation then consists in maximizing the difference between the PDFs inside and outside a contour C, as

$$\arg\min_C\Big\{L(C) - \lambda KL\big(p_{in}(f,C)\|p_{out}(f,C)\big)\Big\}, \tag{5}$$

where $L(C)$ is the length of the contour, and λ is a regularization parameter. After computing the shape derivative, Bresson *et al.* [8] showed that the minimization of the energy in Equation (5) can be solved by a variational model, enabling the fast computation of a global optimum.

The contribution of this paper is to propose a new texture segmentation approach by relying on an ellipse-based texture representation, where ellipses are regarded as texture elements. We argue that natural texture images can be approximated well by a tree of ellipses and the boundaries between two texture regions can be identified by grouping these ellipse ensembles according to some statistical properties with an active contour model. This work somehow fills the gap between granulometry and texton theory on segmentation. Thanks to the ellipse-based features, which might be non-local, the segmentation method can integrate local and global information in the image. Furthermore, the proposed approach is flexible: it allows to segment images subjected to scaling and rotations and it is robust to illumination changes inside the image. In this paper, we also adapts the KL-divergence based active contour model to multi-features, which enables us to take into account different texture cues for segmentation.

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