Joint estimation of local variance and local regularity for texture segmentation.

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Texture segmentation constitutes a task of utmost importance in statistical image processing. In this work, particular attention is granted to a class of multiscale techniques relying on scale-free local features [1] to characterize textures. The present study renews this recurrent topic by proposing an original approach enrolling jointly scale-free and local variance descriptors into a convex, but non smooth, minimization strategy.

Texture characterization and mathematical modeling – We consider piecewise monofractal textured images $x = (x_{\underline{n}})_{\underline{n}\in\Omega} \in \mathbb{R}^{|\Omega|}$ of size $|\Omega| = N_1 \times N_2$, , characterized by the statistical properties of their multiscale coefficients $\left(\mathcal{X}_{\underline{n}}^{(j)}\right)_{\underline{n}\in\Omega, j\in\mathbb{N}^*}$, where 2^j denotes the scale. These multiscale coefficients consist of wavelet leaders of texture x [1], and behave locally as

$$\log_2 \mathcal{X}_{\underline{n}}^{(j)} \simeq \log_2 s_{\underline{n}} + j h_{\underline{n}} \quad \text{as} \quad 2^j \to 0, \tag{1}$$

where $s \in \mathbb{R}^{|\Omega|}$, the local variance, and $h \in \mathbb{R}^{|\Omega|}$, the local regularity, are assumed to be piecewise constant fields. It is not assumed a priori that both s and h have edges at same locations. In this context, performing texture segmentation thus consists in estimating sharp changes in s and h from image x.

Estimation of s and h – The most direct way to estimate $s_{\underline{n}}$ and $h_{\underline{n}}$ from the relation (1) is to perform a linear regression over scales j. Yet it gives very noisy estimates, as shown in Fig. 1. The model (1) is thus embedded into an optimization procedure, including penalization favoring piecewise constancy of s and h. To built a convex functional, we set $\log_2 s_{\underline{n}} = v_{\underline{n}}$ and find

$$\left(\widehat{v}, \widehat{h}\right) \in \underset{v,h}{\operatorname{Argmin}} \sum_j \|\log_2 \mathcal{X}^{(j)} - v - jh\| + \zeta \mathrm{TV}(v) + \eta \mathrm{TV}(h). \tag{2}$$

Joint estimates of local variance $\widehat{s} = 2^{\widehat{v}}$ and local regularity $\widehat{h}$ are presented in Fig. 1. Moreover, since the functional (2) is strongly convex, it is possible to design a fast algorithm and thus to analyze high resolution images in a reasonable time.

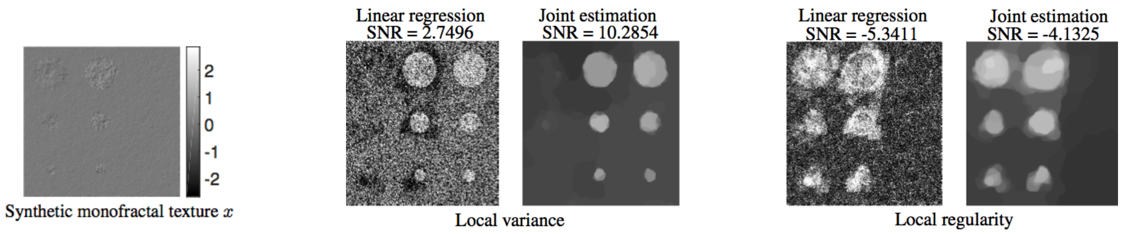

Figure 1: Texture x and estimates for local variance s and regularity h.

Contribution – In this work, we propose a new estimation/segmentation procedure that perform jointly the estimation of h of s. The proposed method aims (i) to estimate simultaneously the local variance and the local regularity, (ii) to rely on a fast algorithmic procedure and (iii) to involve a limited amount of memory.

Joint work with: Patrice Abry, Nelly Pustelnik.

References

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