Unsupervised Texture Segmentation using Active Contours and Local Distributions of Gaussian Markov Random Field Parameters

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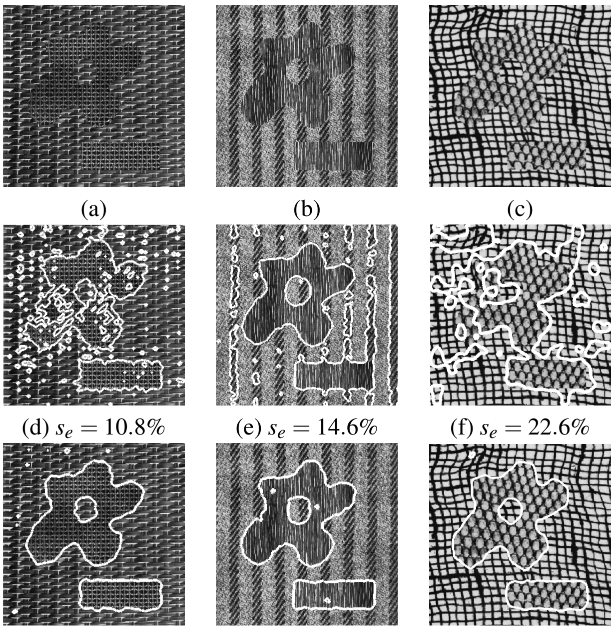
Gaussian Markov Random Fields (GMRF) have been exploited for modeling textures and extracting effective texture features [1, 2]. Model parameter estimates of low order GMRF have been widely used as the conventional texture feature for texture image segmentation [6]. The drawbacks of these features are firstly, their discriminative ability highly depends on model selection, yet is restricted to low order models due to computational concerns [2, 5]. Secondly, sufficiently large estimation windows should be selected to well characterize the given texture yet compromising accurate boundary localization [6]. Also the fact that the estimated model parameters obey a certain probability distribution for a given texture [3], has never been exploited when obtaining these features.

In this paper, instead of using model parameters as texture features, we exploit the variations in low order GMRF parameter estimates, obtained through model fitting in local region around the given pixel. A spatially localized estimation process is carried out by using a moderately small estimation window and modeling partial texture characteristics belonging to the local region through maximum likelihood method. Hence the estimated values inherit significant fluctuations, spatially, which can be related to texture pattern complexity. The variations occur in estimates are quantified by normalized local histograms, maintaining simplicity and efficiency and are named as PL histograms here. Selection of an accurate window size for histogram calculation is very important for a better segmentation. Since the variations occurred in estimates have a correlation with the texture pattern, the correct window size is assumed to be nearly equal to the average texture pattern size of the image. It is found via a method based on the entropy of the texture image.



(a) (b) (c)

(d) $s_e = 10.8\%$ (e) $s_e = 14.6\%$ (f) $s_e = 22.6\%$

(g) $s_e = 1.68\%$ (h) $s_e = 1.09\%$ (i) $s_e = 2.54\%$

Figure 1: Segmentation of large and medium size texture patters with low order GMRF. (a)-(c) original images, (d)-(f), conventional GMRF features [1] and (g)-(i) PL histogram. s_e- segmentation error.

The novel features capture the variations that occur in model parameters which provide useful information for texture segmentation. In CGMRF features these important features are smoothed out by the estimation process. Formulation of PL histogram involves using small neighborhood sizes and estimation window sizes, hence giving lower computational cost and better boundary localization. They extend the possibility of using low order GMRF for segmenting fine to very large texture patterns (figure 1) and also improving the segmentation of textures with close characteristics (figure 2).

(a) (b) (c) $s_e = 17.9\%$ (h) $s_e = 7.03\%$

Figure 2: Segmentation of images with close component textures. (a) original images, (b) segmentation target, (c) Gabor features and (d) PL histograms.

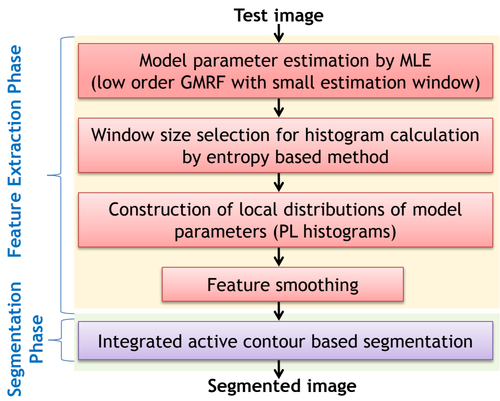


Figure 3: Proposed texture feature extraction and segmentation algorithm.

Extracted features are smoothed using diffusion via Beltrami flow and directed to the integrated active contour model [4] for unsupervised texture segmentation. The proposed method is illustrated in figure 3. Experimental results on statistical and structural component textures show improved discriminative ability of the features compared to some recent algorithms in the literature.

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