Bimodal Texture Segmentation with the Lee-Seo Model

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Abstract. This paper presents a novel approach to bimodal texture segmentation. The proposed approach features a local binary pattern-based scheme to transform bimodal textures into bimodal gray-scale intensities, segmentable by the Lee-Seo active contour model. This process avoids the iterative calculation of active contour equation terms derived from textural feature vectors, thus reducing the associated computational overhead. The proposed approach is region-based and invariant to the initialization of the level-set function, as it converges to a stationary global minimum. It is experimentally validated on 18 composite texture images of the Brodatz album, obtaining high quality segmentation results, whereas the convergence times are up to an order of magnitude smaller than the ones reported for other active contour approaches for texture segmentation.

Keywords: Texture Segmentation, Local Binary Patterns, Active Contours.

1 Introduction

Active contour models have been extensively applied for texture segmentation in the recent years [1]-[5]. Despite their numerous advantages, such as contour smoothness, noise robustness and topological adaptability, these models usually involve an energy functional, which converges to a local minimum, not necessarily corresponding to the target boundaries. Active contour models designed so as to obtain a global minimum would allow the development of integrated texture segmentation approaches, which could be reliably applied in various domains including medical image analysis, industrial monitoring of product quality, content-based image retrieval, and remote sensing.

The main idea in the active contour approach involves the deformation of initial contours towards the boundaries of the image regions to be segmented. A well known active contour model, introduced by Chan and Vese [6] has received considerable attention due to its advantages: 1) it is region-based, enabling the delineation of regions defined by smooth intensity changes, and 2) its level set formulation provides adaptability to topological changes. However, the Chan-Vese model does not guarantee convergence to a global minimum, whereas contour evolution depends on the intensities rather than on the textural content of the image to be segmented.

Recently, a modified version of the Chan-Vese model has been proposed by Lee and Seo [7], designed so as to obtain a stationary global minimum. This attribute

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guarantees that a vision system employing Lee-Seo model is capable of reliably capturing the desired boundaries. Moreover, the stationarity of its associated solution facilitates the imposition of a reasonable termination criterion on the algorithm, contributing to its efficiency.

State of the art research in active contour models has concentrated on the use of texture as a guiding force to contour evolution. Most of the previous active contour approaches for texture segmentation involved Gabor and wavelet features [1]-[3]. The Local Binary Pattern (LBP) operator [8], offers an alternative approach for texture representation. Unlike the Gabor features, which are calculated from the weighted mean of pixel values over a small neighborhood, LBP considers each pixel in the neighborhood separately, providing even more fine-grained information. In addition, the LBP texture features are invariant to any monotonic change in gray level intensities, resulting in a more robust representation of textures under varying illumination conditions. Comparative studies have demonstrated that the use of LBP features may result in higher classification accuracy than the Gabor and wavelet features, with a smaller computational overhead [8]-[10].

In this paper we propose a novel approach for bimodal texture segmentation that incorporates an LBP-based representation of textures under a Lee-Seo segmentation framework. The proposed approach encodes the spatial distribution of the most discriminative LBPs of an input image into gray-level intensities producing a new image, which is subsequently segmented by the Lee-Seo model. This approach avoids the iterative calculation of active contour equation terms derived from textural feature vectors, reducing the associated computational overhead. However, the proposed approach maintains high segmentation quality, taking advantage of the region-based, level-set formulation of the Lee-Seo model, as well as of its convergence to a stationary global minimum.

The rest of this paper is organized in five sections. Sections 2 and 3 provide an outline of the Lee-Seo model and the LBP features respectively. Section 4 describes the proposed approach, whereas the results from its application on bimodal textures are apposed in Section 5. Finally, in Section 6 the conclusions of this study are summarized.

2 Lee-Seo Active Contour Model

The Lee-Seo model as posed in [7] can take the form of a minimization problem: if Ω is considered as a bounded open subset of R^2, with $\partial\Omega$ the boundary, we seek for $\inf F(c^+, c^-, C)$:

$$F'(c^+,c^-,C) = \mu \cdot length(C) + \lambda^+ \int_{in(C)} |u_0(x,y) - c^+|^2 \phi(x,y) H(a + \phi(x,y))dxdy$$
$$- \lambda^- \int_{out(C)} |u_0(x,y) - c^-|^2 \phi(x,y) H(a - \phi(x,y))dxdy \qquad (1)$$

where $u_0 : \Omega \to R$ is the given image, ϕ is the level-set function introduced in [11], $C(s):[0,1] \to R^2$ a piecewise parameterized curve, c^+ and c^- are unknown constants representing the average value of u_0 inside and outside the curve, α is an arbitrary small positive value, and parameters $\mu > 0$ and $\lambda^+, \lambda^- > 0$ are weights for the regularizing term and the fitting terms, respectively.

Keeping c^+ and c^- fixed, and minimizing F with respect to ϕ, we deduce the associated Euler-Langrange equation for ϕ. Parameterizing the descent direction by an artificial time $t \geq 0$, the equation in $\phi(t, x, y)$ (with $\phi(0, x, y) = \phi_0(x, y)$ defining the initial contour) is

$$\frac{\partial \phi}{\partial t} = \delta(\phi)\{\mu \cdot div(\frac{\nabla \phi}{|\nabla \phi|}) - \lambda^+ |u_0 - c^+|^2 [H(a+\phi) + \phi H'(a+\phi)]$$
$$+ \lambda^- |u_0 - c^-|^2 [H(a-\phi) + \phi H'(a-\phi)]\} \tag{2}$$
$$\phi(0, x, y) = \phi_0(x, y)$$
$$t \in (0, \infty), (x, y) \in \Omega$$

The stationarity of the global minimum obtained at the convergence of the Lee-Seo model allows the imposition of a termination criterion. For example, as $|\phi(x, y)|$ converges to α, the Normalized Step Difference Energy (NSDE) can be defined as follows:

$$NSDE = \frac{|\phi(x, y) - a|^2}{|\phi(x, y)|^2} \tag{3}$$

The NSDE is calculated at each iteration and as soon as it becomes smaller than an experimentally determined constant, the algorithm is terminated.

3 Local Binary Patterns

We adopt the formulation of the LBP operator defined in [8]. Let T be a texture pattern defined in a local neighborhood of a grey-level texture image as the joint distribution of the gray levels of P ($P > 1$) image pixels:

$$T = t(g_c, g_0, ..., g_{P-1}) \tag{4}$$

where g_c is the grey-level of the central pixel of the local neighborhood and g_p (p = 0,..., P-1) represents the gray-level of P equally spaced pixels arranged on a circle of radius R ($R > 0$) that form a circularly symmetric neighbor set.

Much of the information in the original joint gray level distribution T' is conveyed by the joint difference distribution:

$$T' \approx t(g_0 - g_c, ..., g_{P-1} - g_c) \tag{5}$$

This is a highly discriminative texture operator. It records the occurrences of various patterns in the neighborhood of each pixel in a P-dimensional vector.

The signed differences g_p-g_c are not affected by changes in mean luminance, resulting in a joint difference distribution that is invariant against gray-scale shifts. Moreover, invariance with respect to the scaling of the gray-levels is achieved by considering just the signs of the differences instead of their exact values:

$$T'' \approx t(s(g_0 - g_c),...,s(g_{P-1} - g_c)) \tag{6}$$

where

$$s(x) = \begin{cases} 1 & ,x \geq 0 \\ 0 & ,x < 0 \end{cases} \tag{7}$$

For each sign $s(g_p\text{-}g_c)$ a binomial factor 2^p is assigned. Finally, a unique $LBP_{P,R}$ value that characterizes the spatial structure of the local image texture is estimated by:

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^p \tag{8}$$

The distribution of the $LBP_{P,R}$ values calculated over an image region, comprises a highly discriminative feature vector for texture segmentation, as demonstrated in various studies [8]-[10].

4 Proposed Approach

The underlying idea of the proposed approach is to encode the spatial distribution of the most discriminative $LBP_{P,R}$ values of an input image into gray-level intensities so as to produce a new image that satisfies the assumption of approximately piecewise constant intensities. This is a basic assumption of the active contour model, which is subsequently applied on the new image. As this approach avoids the iterative calculation of active contour equation terms derived from textural feature vectors, the proposed approach can be more efficient than other active contour approaches.

The proposed algorithm begins with the calculation of the $LBP_{P,R}$ values of all pixels of the input image I. A binary image is assigned to each of the existent LBP values. For each $i = LBP_{P,R}(x,y)$, the pixel (x,y) of the binary image B_i is labeled white, indicating the presence of the LBP value i, otherwise it is labeled black.

In the sequel, each B_i is divided into constant-sized blocks and the number $P_{white}(i,j)$ of white pixels contained in each block j of B_i is counted. Since white pixels in B_i indicate the presence of the LBP value i, their density may vary for regions of different texture, characterized by different LBP distributions. The maximum inter-block difference of white pixel densities in B_i, as expressed by contrast index ξ_i:

$$\xi_i = \max_j(P_{white}(i,j)) - \min_j(P_{white}(i,j)) \tag{9}$$

can be used for the discrimination of bimodal textures. The contrast index ξ_i is expected to be smaller if white pixels are mainly concentrated in some image blocks, indicating that the associated LBP value characterizes the texture of an image region. Otherwise, if the white pixels are entangled within the blocks and cannot be associated with the texture of an image region, the contrast index ξ_i is expected to be increased.

The binary images B_i, i=1,2,…2^p are sorted according to their contrast index ξ_i, and the r top-ranked images are selected. The logical OR operator is applied on all combinations K of the selected r binary images. The resulting "cumulative" binary images CB_k, k=1,2,…K, contain information derived from subsets of the existent LBPs. This is in agreement with [8], according to which an appropriately selected subset of LBPs maintains most of the textural information associated with the set of the existent LBPs. The "cumulative" binary image CB_m with the maximum contrast index is selected, according to:

$$m = \arg_k(\max(\xi_k)) \tag{10}$$

This image will be comprised of regions characterized by distinguishable white pixel densities, associated with different textures. Equation (10) imposes that the binary images B_i used to generate CB_m, have their highest white pixel densities on regions of the same texture.

In order to limit the effect of local variances in the spatial frequency of the LBPs, a Gaussian kernel W_G is convolved with CB_m. This results in a smoothed image CB_G of nearly homogeneous image regions, which satisfy the assumption of Lee-Seo model for piecewise constant intensities. Such smoothing operations have been proved to enhance texture discrimination, as the notion of texture is undefined at the single pixel level and is always associated with some set of pixels [12]. Moreover, convolution with Gaussian kernel W_G ensures that the gray level of each pixel in the smoothed image CB_G depends on the distances of the local binary patterns, which are present in the neighborhood of the pixel and have been associated with the texture of interest in the previous steps of the algorithm. Finally, it should be taken into account that smoothing accelerates the convergence of the subsequently applied active contour. Fig. 1 illustrates an example of an original image composed of Brodatz textures, along with the resulting smoothed image CB_G.

In the final step, the Lee-Seo model is applied to CB_G. The region-based formulation of this active contour model enables the segmentation of an image into two discrete regions, even if these regions are not explicitly defined by high intensity gradients. In addition, its level set formulation allows the Lee-Seo model to adapt to topological changes, such as splitting or merging, in case regions of the same texture are interspersed in the image. Finally, the Lee-Seo model is guaranteed to converge to a stationary global minimum.

The steps of the proposed algorithm can be summarized as follows:

```
1.      Calculate LBP values
        For each pixel (x,y) in I Calculate LBP_{P,R}(x,y)
2.      Generate binary images B_i, i = 1,2,…,2^P
        Initialize B_i(x,y) = 0
        For each LBP_{P,R}(x,y) do
          i = LBP_{P,R}(x,y)
          B_i(x,y) = 1
        End
3.      Generate "cumulative" binary image CB_m
        Rank all B_i according to ξi
        For each combination COMB_k={B_i1, B_i2,… ,B_il},
        k = 1,2,…K, l = card(COMB_k) of the r top-
        ranked B_i do
          CB_k = (B_i1 OR B_i2 OR … OR B_il)
        End
        Find CB_m using (12)
4.      Smoothing and segmentation
        CB_G = CB_m * W_G
        Segment CB_G using the Lee-Seo model.
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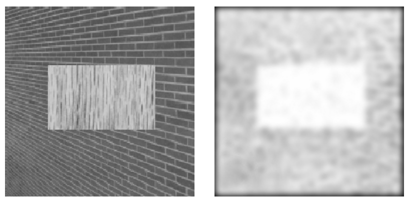
5 Results

Experiments were performed to investigate the performance of the proposed approach on texture segmentation. The dataset used is comprised of 18 composite texture images from the Brodatz album [13]. The proposed approach was implemented in Microsoft Visual C++ and executed on a 3.2 GHz Intel Pentium IV workstation. As a segmentation quality measure, the overlap q was considered:

$$q = \frac{A \cap G}{A \cup G} \tag{11}$$

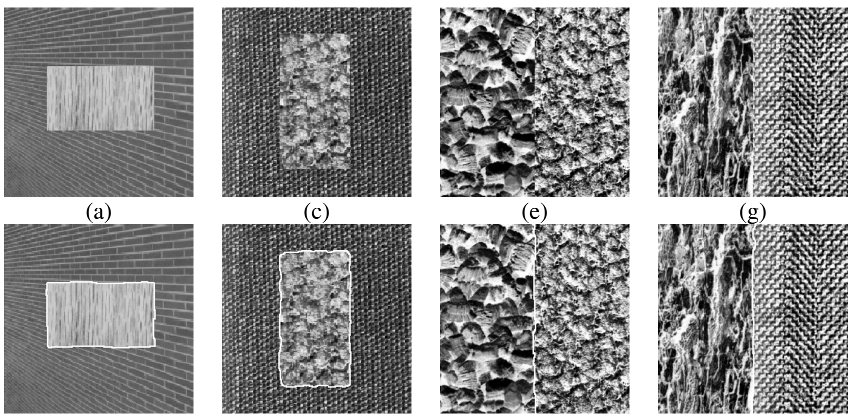
where A is the region delineated by the approach and G is the ground truth region.

The LBP operator considered in the experiments was $LBP_{8,1}$. The block size used was set to 16×16, and a number of r=5 top-ranked binary images (see Section 4) was found to be sufficient for the performed segmentation tasks.



(a) (b)

Fig. 1. Example of a smoothed image $CB_{G,}$ generated in step 4 of the proposed algorithm, (a) original image composed of Brodatz textures, (b) corresponding image CB_G



(a) (c) (e) (g)

(b) (d) (f) (h)

Fig. 2. Segmentation results of the application of the proposed approach for bimodal texture segmentation, (a,c,e,g) original images composed of Brodatz textures, (b,d,f,h) segmented images

Figure 1 illustrates an example of an original image composed of Brodatz textures, along with the resulting smoothed image CB_G, which is generated in step 4 of the proposed algorithm. Figure 2 illustrates four examples of the application of the proposed approach for bimodal texture segmentation. The segmentation results obtained are very promising, with the frames composed of different texture patterns being successfully segmented. The overlaps measured are 99.1%, 96.9%, 99.7%, and 99.1% for the segmentations illustrated in Fig. 1b, 1d, 1f, and 1h respectively, whereas the average overlap obtained was 98.9±0.7%. The convergence times observed for the available images, ranged between 2 and 3 seconds depending on the complexity of the target boundaries. These convergence times are an order of magnitude smaller than the ones reported in other active contour approaches for texture segmentation [2].

6 Conclusion

In this paper, we presented a novel approach for bimodal texture segmentation. The proposed approach features a local binary pattern scheme to transform bimodal textures into bimodal gray-scale intensities, segmentable by the Lee-Seo active contour model. This process avoids the iterative calculation of active contour equation terms derived from textural feature vectors, thus reducing the associated computational overhead. In addition, the region-based, level-set formulation of the Lee-Seo model allows segmenting regions defined by smooth intensity changes, as well as adapting to topological changes. Finally, the Lee-Seo model is invariant to the initialization of the level-set function and guarantees convergence to a stationary global minimum. The stationarity of the associated solution facilitates the imposition of a reasonable termination criterion on the algorithm, contributing to its efficiency.

In our experimental study, the proposed approach achieved very promising segmentation results, whereas the required convergence times were an order of magnitude smaller than the ones reported in other active contour approaches for texture segmentation [2].

The proposed approach in its current form is limited to bimodal segmentation. However, future perspectives of this work include an extension for multimodal texture segmentation, as well as applications on various domains, and incorporation of the uniform LBP operator, introduced in [8].

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