Segmentation of Color Textile Images Based on a Multiscale Context Model

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Abstract

In this paper, a multiscale color image segmentation algorithm based on a contextual model for textile images corrupted by textile texture noise is proposed. The context model not only captures the statistical dependency between adjacent scales, but also the statistical dependencies among the neighboring blocks. The multiscale approach is used to solve the conflict between boundaries localization and high resolution segmentation, and the segmentation result is recursively refined at each scale based on the contextual model. Experimental results show that our algorithm can achieve better segmentation results when tested on color textile images, and also produce high quality edge images when compared with the mean-shift algorithm[1] and the multiscale block segmentation approach proposed in [2].

1 Introduction

Color segmentation is an extremely important operation in several applications of image processing and computer vision, especially in the textile and printing manufacture industry, since it represents the very first step of textile pattern design and print. The essential goal of color segmentation in the textile and printing manufacture industry is to extract the dominant colors from a textile image which was obtained by scanning a cloth sampling into the computer. At the same time it demands the segmented image will produce a smooth and connective edge image which will be useful for pattern editing and designing later.

In a textile color image, the fabric texture has a great impact on the colors' appearance, which is known as the "texture noise". A color textile image is shown in Fig. 1. According to the human observation there are only 6 dominant colors in the original textile image (left), but if the small window in the left image is enlarged, we will find there are many different colors in the perceived red region. This phenomenon was caused by the "texture noise".

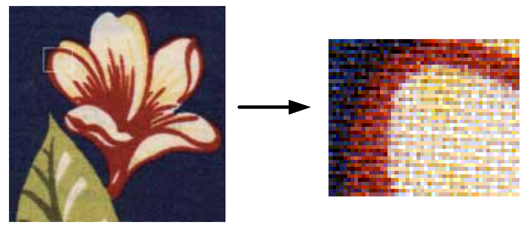

Fig. 1 Example of texture noise

The flatness of the color histogram of a textile image makes bottom-up, solely image driven segmentation techniques always prone to errors. A relatively simple but quite effective technique to obtain the dominant colors from a color image is the color segmentation algorithm proposed by Comaniciu and Meer [1]. It is based on the "mean shift" algorithm for estimating the density gradients, and essentially works with the image histogram, and it also attempts to incorporate spatial constraints by imposing constraints on the connectivity of the detected regions. However it is difficult for the clustering-based algorithms to capture the global dominant colors from a textile image because of the texture noise. The experimental results in Section 4 show that the mean-shift algorithm is not good at extracting the true dominant colors from the textile image, and the detected edge image is of poor quality.

Another very important image segmentation technique which can integrate both image features and prior contextual properties — multiscale Bayesian approaches have become popular in recent years. In [3], Markovian dependencies are assumed across scales to capture interscale dependencies of multiscale class labels with a causal MRF structure, and a non-iterative segmentation algorithm (SMAP) was developed with low computation cost. In [4], an improved wavelet-domain HMMs, HMT-3S was developed to capture wavelet coefficient dependencies both across subbands and across scales. The joint multicontext and multiscale segmentation technique for texture images can achieve more accurate texture statistical characterization. All these algorithms were designed for gray images. In [5], a multiscale perceptual segmentation approach for color image textures was proposed. A multiscale tower is generated by a multiband smoothing based on human psychophysical measurements of color appearance. And the probabilistic reassignment of the pixels to the clusters is propagated through levels of the multiscale tower.

Although our segmentation method is based on a contextual model and multiscale approaches, it has several important distinctions from the previous approaches. First, we will not create a tower of multiscale images based a smoothing algorithm as described in [5]. Our multiscale approach was motivated by a similar context-dependent classification structure developed by Li et al. [6] which was designed for gray low DOF image segmentation. We modified this kind of model for color images, and the probabilities is assigned to the blocks not to the pixels, and balance statistical dependencies between adjacent scales, and among the neighboring blocks into the MAP estimation, but in [2] we had not introduced any statistical dependencies among scales and adjacent blocks. The concept of scale in this paper is related to the size of blocks during the segmentation.

The rest of paper is organized as follows: In Section 2 we describe the multiscale contextual model used in our segmentation algorithm. The details of the segmentation algorithm are provided in Section 3. Section 4 reports experimental results of our algorithm on color textile images, compared with the state of the art algorithms, and Section 5 ends the paper by presenting some concluding remarks.

2 The Multiscale Contextual Model

Xia et al. proposed five context models in [4], and they proved that the context-4 model can provide high percentage of boundaries that coincide with the true ones. In this paper, we adopted the context-4 model shown in Figure 2. But there are fundamental distinctions between our model and the context model proposed in [4]: their multiscale decomposition was based on the Gaussian pyramid, and the interscale and the intrascale statistical dependencies of multiscale class labels were quite different from that derived here. The most important difference between the context model proposed in [4] and our context model is that their model only used for gray images.

We start with a large block size. And the color of each block is initially determined by the color distribution of the block and the color features of the pre-computed dominant colors (which will be described in the next section).

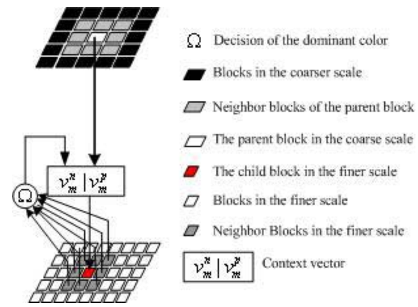

Fig.2 The Multiscale context model

At every increased scale, each block is subdivided into four child blocks, forming a quadtree structure. If a block is decided as smooth, and this block inherits the color of its parent block; otherwise if the block is nonuniform, and the color of this block will be computed as the following equation:

$$c_{d_{ij}} = \arg\max_{k=1,2,\cdots M} p(d_{ij} \mid \mathbf{c}_k) p(\mathbf{c}_k \mid \mathbf{v}_k), \quad (1)$$

where M is the total number of the extracted dominant colors from the input image, $p(d_{ij} \mid \mathbf{c}_k)$ is the conditional probability of the current block d_{ij} will be classified as the *kth* dominant color, given the color features of the dominant colors:

$$p(d_{ij} \mid \mathbf{c}_k) = \frac{\#(|\mathbf{p}_{mn} - \mathbf{c}_k| < T_k, \mathbf{p}_{mn} \in d_{ij})}{S \times S} \quad (2)$$

Here $\mathbf{p}_{mn}$ is represented as the RGB vector of a pixel located in the current block d_{ij}, and # is the operator to count how many pixels in the current block belong to the *kth* dominant color ($S\times S$ is the total number of pixels in the current block d_{ij}). $\mathbf{c}_k (k = 1, \cdots, M)$ represent the pre-computed color feature vectors of the dominant colors. And T_k takes a half of the minimum distance between the dominant color $\mathbf{c}_k$ and the other dominant colors:

$$T_k = \min_j \frac{\|\mathbf{c}_k - \mathbf{c}_j\|}{2} \quad (3)$$

Thus all the pixels belong to the dominant color $\mathbf{c}_k$ will fall into a sphere with radius of T_k which centered at $\mathbf{c}_k$. $\mathbf{v}_k$ in equation (1) contains the contextual information including the color information of the parent block and its 8 adjacent blocks. We make the assumption of the independence of the color conditional probability of the parent block from those of the neighbor blocks. Hence

$$P(\mathbf{c}_k \mid \mathbf{v}_k) = P(\mathbf{c}_k \mid \mathbf{v}_k^p) \cdot P(\mathbf{c}_k \mid \mathbf{v}_k^n) \quad (4)$$

Either $P(\mathbf{c}_k \mid \mathbf{v}_k^p)$ or $P(\mathbf{c}_k \mid \mathbf{v}_k^n)$ can be computed as the following:

$$p(\mathbf{c}_k \mid \mathbf{v}_k) = \frac{p(\mathbf{c} = \mathbf{c}_k)\, p(\mathbf{v} = \mathbf{v}_k \mid \mathbf{c} = \mathbf{c}_k)}{\sum_{j=1}^{M} p(\mathbf{c} = \mathbf{c}_j)\, p(\mathbf{v} = \mathbf{v}_k \mid \mathbf{c} = \mathbf{c}_j)} \quad (5)$$

and the prior probability of the dominant colors $p(\mathbf{c} = \mathbf{c}_k)$ can be computed at the beginning according to equation (2), but here d_{ij} is the whole image.

In the process of segmentation, first we choose a uniform texture region as a texture sample from the input image, and then apply the wavelet transform on its luminance component, and obtain three variances of wavelet coefficients in the three high frequency bands σ_t^{LH}, σ_t^{HL} and σ_t^{HH}, which is used as a uniform texture feature vector. We will use this texture feature to decide whether a block is uniform or not during the segmentation. In our current implementation, the Haar wavelet transform is used because of its good localization property provided by its shorter filter and its low computation cost.

3 The Segmentation Algorithm

Our algorithm focuses on the textile color images segmentation based on the contextual model described above through a multiscale approach which consists of three steps:

1) Extraction of the dominant colors;

2) Crude segmentation at the lowest scale;

3) A recursive process to adjust the crude segmentation results using a multiscale approach.

3.1 Extraction of Dominant Colors

A uniform color region is selected according to the human observation. And the wavelet transform is applied to the region. The mean values of wavelet coefficients in the low frequency bands of the RGB three channels is used as the color feature for the dominant colors $\mathbf{c}_k (k = 1, \cdots, M)$. Repeat the above process until all the dominant colors according to the human observation are extracted.

3.2 The Crude Segmentation

We started with a large block size $S^{(1)} \times S^{(1)}$, Denote the set of blocks at scale r by $S^{(r)}$, $r = 1, \cdots, R$, where R is the maximum scale set by the user. We chose R as the scale at which one block is a single pixel in our applications. The dominant color in each crude block is computed as following:

$$c_{d_{ij}} = \arg\max_{k=1,2,\cdots M} p(d_{ij} \mid \mathbf{c}_k) \quad (6)$$

The three variances of wavelet coefficients in the three high frequency bands of the luminance component of the block is used as the texture feature for the block, and the uniform factor is defined as:

$$s(\sigma_{d_{ij}}^{LH}, \sigma_{d_{ij}}^{HL}, \sigma_{d_{ij}}^{HH}) = \frac{\sigma_{d_{ij}}^{LH}}{\sigma_t^{LH}} \cdot \frac{\sigma_{d_{ij}}^{HL}}{\sigma_t^{HL}} \cdot \frac{\sigma_{d_{ij}}^{HH}}{\sigma_t^{HH}} \quad (7)$$

As we know if the block is with uniform texture, the factor $s(\sigma_{d_{ij}}^{LH}, \sigma_{d_{ij}}^{HL}, \sigma_{d_{ij}}^{HH})$ will be around 1. And if an initial block which is satisfied with the following two conditions:

$$T_{11} < s(\sigma_{d_{ij}}^{LH}, \sigma_{d_{ij}}^{HL}, \sigma_{d_{ij}}^{HH}) < T_{22} \quad (8)$$

$$\sigma_{ij}^{LL} < \sigma_k^c + t_1 \quad (9)$$

The block will be judged as a smooth block; otherwise this block is considered as nonuniform. Here σ_k^c and σ_{ij}^{LL} are the variances of wavelet coefficients in the low frequency bands of the previously selected dominant color region and the current block respectively, and t_1 usually takes 10 percent of σ_k^c, and T_{11}=0.8 and T_{22} =1.2. And now we obtain a crude segmentation at the lowest resolution.

3.3 Recursive Refining Segmentation

At every increased scale, each block is subdivided into four child blocks, forming a quadtree structure. All child blocks inherit the colors of parent blocks as their initial colors. If the parent block and its 8 adjacent blocks are uniform, and are mapped into the same dominant color, and the block itself satisfies the conditions (8) and (9), then the current block is considered as smooth; otherwise it is nonuniform. For smooth blocks, they inherit the colors of their parent blocks. But for edge blocks, the color distribution should be re-computed according to equation (1). During the segmentation σ_t^{LH}, σ_t^{HL} and σ_t^{HH} should be re-computed at each stage because the uniform texture region need to be subsampled by 2 at every increased scale. This is because at every increased scale, the size of the block will become small, the metric gauge to decide whether the block is smooth or not should also be changed. Repeat the above process, until the highest resolution is reached.

For the highest resolution, the block is degenerated to a single pixel, we set the current pixel to one of the colors of its 8 neighbor pixels which is closest to the central pixel.

4 Experimental Results

In this paper we mainly focus on the segmentation of color textile images. Fig.3 shows the segmented results of three algorithms. In order to compare the segmented results, we detect the edges from the luminance components of the segmented results. In the left column are the segmented results, and in the right are the edge maps. The first row is the segmented results based on the mean-shift algorithm [1], the second row and the third row are the segmented results using the multiscale block segmentation algorithm [2] and the algorithm described in this paper respectively. We can see that our edge images are much smoother than these two techniques. Even using a Gaussian low-pass filter at the previous stage, our segmentation results are also much better than these two methods. Because of the limitation of the length of the paper, there is no space to present many other examples. The last row in Fig.3 shows the segmentation results based on our method after the Gaussian low-pass filtering

5 Conclusions

In this paper, we proposed a contextual model which can effectively model the complex boundary behavior of color textile images. The multiscale approach is used to solve the conflict between boundaries localization and high resolution segmentation. Experimental results show that our algorithm can achieve a high quality edge images when tested on color textile images with the texture noise compared with other segmentation algorithms.

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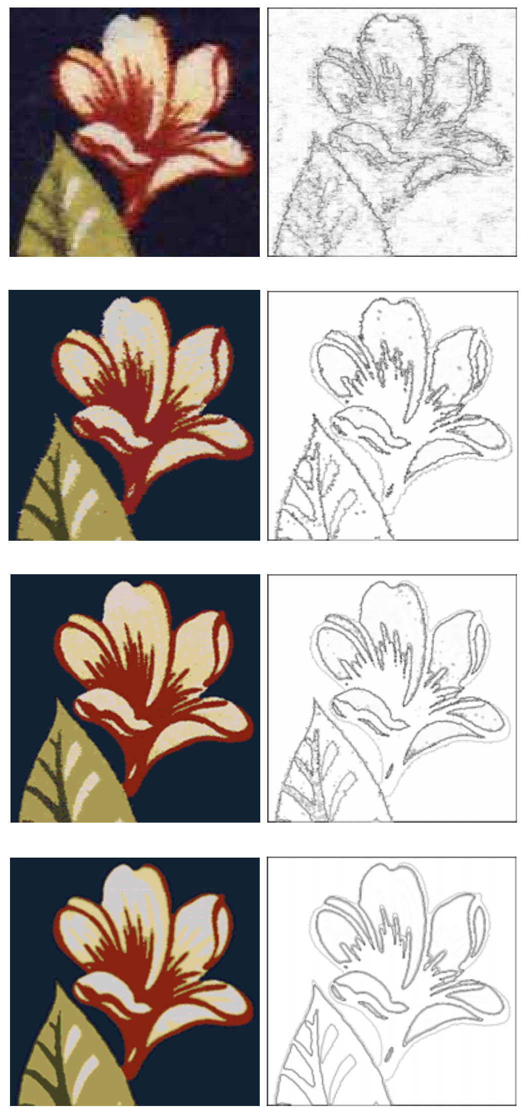

Fig.3 The Segmentation results