Color and/or Texture Segmentation using Deterministic Relaxation and Fast Marching Algorithms

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Abstract

The segmentation of colored texture images is considered. Either luminance, color, and/or texture features could be used for segmentation. For luminance and color the classes are described using the corresponding empirical probability distributions. The Discrete Wavelet Frames analysis is used for obtaining features of texture patterns. At a first stage, pattern analysis is performed for extracting the features using the Bhattacharya distance. Two labeling algorithms are proposed. A deterministic relaxation algorithm using a likelihood based distance yields the labeling of pixels to the different color-texture patterns. In addition, a new multi-label fast marching level set algorithm is utilized for the determination of the segment boundaries.

1. Introduction

In this paper, the problem of image segmentation is approached with the use of texture and color features. Methods for combining color and texture for segmentation have been proposed in the past [6], using *HSV* color space and primitive texture features combined in pointwise expectation maximization clustering.

In our work texture feature extraction is based on the concept of wavelet frames, and color features are based on the *Lab* color space. These features could be used independently or in conjunction for image segmentation depending on the image content.

In this paper a new segmentation scheme is proposed, where two new approaches are introduced: the first one uses a Markov random field model, and the second one a level set method. In both cases the texture feature parameters have to be previously determined. Thus an unsupervised method of feature extraction is proposed. The number of different patterns present in the image is assumed to be known, and the depth of wavelet analysis is given by the user.

Knowing the number of categories, blocks with homogeneous content are extracted and grouped, when they are similar. After clustering these blocks, the feature vector is estimated for each label. At each image point distance measures are defined from the different classes using the negative logarithm of the likelihood of the corresponding feature vector for texture and color features.

When a Markov random model is adopted for the label field, a deterministic relaxation algorithm is applied. Similar work using only Discrete Wavelet Frames (DWF) texture features is reported in [5]. When a level set method is used, a propagation speed is defined for each label at each point according to the *a posteriori* probability. A new multi-label fast marching algorithm is introduced and applied for obtaining the final segmentation map.

The presented work is organized as follows. In the second section, the Discrete Wavelet Frames decomposition, for texture features, and the use of *Lab* color space, for color features, are described. The segmentation algorithms are presented in Section 3, where various results are given on natural scenes.

2. Feature description

2.1. Texture analysis and characterization

The fundamental tools used for processing the texture images are a filter bank and the concept of wavelet frames. Such an analysis is translation invariant, which is a specifically desirable property, in particular for the accurate localization of region boundaries. In addition, the filter bank decomposes the image into orthogonal components. A lowpass filter $H(z)$ and its conjugate quadrature highpass $G(z)$ form the pair of prototype filters for generating the whole filter bank by upsampling, so that the whole range of bands is covered. Cubic splines having interesting scaling properties could be used for designing the pair of prototype filters [10]. Here the fourth-order binomial filter and its conjugate quadrature filter are used,

$$H(z) = \frac{3}{8} + \frac{1}{4}(z + z^{-1}) + \frac{1}{16}(z^2 + z^{-2}) \quad (1)$$
$$G(z) = zH(-z^{-1}) \quad (2)$$

The filter bank is obtained recursively, indexed by the scale factor $i = 0, \ldots, I$,

$$H_{i+1}(z) = H(z^{2^i})H_i(z) \quad (3)$$
$$G_{i+1}(z) = G(z^{2^i})H_i(z) \quad (4)$$

where $H_0(z) = 1$. Such filters can form orthogonal wavelet basis functions, which decompose the input signal into wavelet coefficients corresponding to different scales.

The above formulation extends to 2-D yielding wavelet bases, which result from the cross product of separable bases in each direction, thus providing a computationally efficient analysis.

The texture content is then characterized by the variances of the detail components of the wavelet coefficients. This characterization is based on the fact that the expected mean value of the details is zero, because $G_i(1) = 0$, and that the different components are uncorrelated, since the values of the covariance matrix except the diagonals are practically zero.

2.2. Color features

Lab color space, being perceptually uniform, was used for color feature extraction. Because luminance component is used in texture analysis and is contained in the approximation component, only chromaticity components (a, b) are used. For image classification using color it is preferable to consider only the chromaticity distribution of an image disregarding luminance. In our work the local 2-D histograms of the (a, b) components were used as features. When some model of the distribution of the (a, b) histograms is fit (e.g. Gauss) the parameters of the model are used as the features. Often though no such modeling is feasible, whence local histogram estimation is required, making the procedure time consuming. The histograms are smoothed with a Gauss kernel to improve statistical robustness.

An adaptation of the Bhattacharya measure with respect to histograms is used to estimate distances between color patterns

$$d_{hist} = -\ln\left(\sum_i \sqrt{h_1(i)h_2(i)}\right) \quad (5)$$

where i indexes the bins of the normalized histograms h_1, h_2. In the case where Gauss modeling is adopted and all components are uncorrelated, as in DWF texture features, the expression becomes

$$d_{12}^B = \frac{1}{2}\sum_{i=1}^{N} \ln \frac{\sigma_{i,1}^2 + \sigma_{i,2}^2}{2\sigma_{i,1}\sigma_{i,2}} + \frac{1}{4}\sum_{i=1}^{N} \frac{(\mu_{i,1} - \mu_{i,2})^2}{\sigma_{i,1}^2 + \sigma_{i,2}^2} \quad (6)$$

where N is the dimension of the feature vector and $\sigma_{i,1}^2$ and $\sigma_{i,2}^2$ the feature variances. When both color and texture are used, the respective features are additively combined.

3. Segmentation algorithms

In this work, only the number of different color-texture classes is assumed to be known. The segmentation could be based on either luminance, color, and/or texture. Any combination of them could be also user-selected. The empirical probability distributions of luminance and color, and the variances of the texture components are estimated using a learning process, which is described below. The mean value of the approximation component of DWF analysis is also estimated and taken into consideration, if it is sufficiently discriminating. The option of two different approaches is given. The feature parameter estimation stage is the same for both. The two proposed methods differ on the determination of the pixel's label, even though it is based, in both cases, on the *a posteriori* probability of the label. The first one adopts a Markov random field model for the labels, while the other assumes that the region boundaries are suitably defined level sets.

3.1. Automatic feature extraction

The first objective is to find the regions of the images which yield the best representative characteristics. For this purpose, the image is divided into blocks. Non homogeneous blocks could be ignored for estimating the characteristics of a specific pattern. If a block is homogeneous, it will be similar to the majority of its neighbouring blocks. The similarity could be measured by the Bhattacharya distance.

All available blocks are sequentially grouped using again the Bhattacharya distance. In order to estimate the feature vectors of the different patterns in the image, a hierarchical clustering algorithm [3] is applied. The procedure terminates when the number of vectors becomes equal to the number of the different classes in the image to be segmented. The feature parameters are estimated at the end of this procedure.

Taking into consideration all parameters characterizing a pattern, a given point belongs to one of the classes if its distance from that class is minimal. The distance is defined using the negative logarithm of the likelihood function of the class label. Due to statistical errors on the distance measure, a 2-D median filter could be applied to each distance array of pixels from each class. Averaging the distances provides more reliable distance measures, and in the presence of region boundaries the median filter should be preferred to a linear filter. This yields smoothed distance arrays, thus compensating for the statistical errors.

3.2. Pixel labeling using deterministic relaxation

As the point classification could give many errors, a relaxation algorithm for pixel labeling may be used. A Bayesian approach is adopted based on a Markov random field (MRF) model of the texture labels. The maximization of the *Maximum A Posteriori* Probability (MAP), or equivalently the minimization of the cost function may be performed using either stochastic relaxation algorithms [4], or deterministic relaxation algorithms as the *Highest Confidence First (HCF)* algorithm [2], or the *Iterated Conditional Modes (ICM)* algorithm [1]. In our work we have used the ICM algorithm. Results of this algorithm are shown in Fig. 1 where the *SeaStones* image is segmented in three classes using 3 levels in DWF decomposition and color modeled as a Gaussian distribution, yielding 11 distinct features. Substantial improvement was observed when color features were added, since the used model is an acceptable approximation of the actual data distribution. The inherent difficulty in segmenting the current image should be noted, which is augmented by the inhomogeneity of the upper class which occurs in both texture and color.

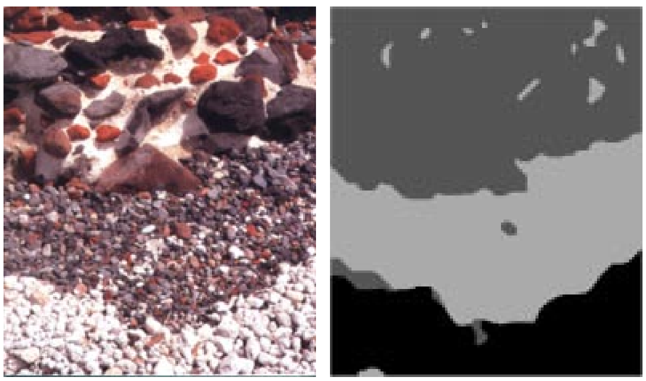

Figure 1. Segmentation of the *SeaStones* image using the ICM algorithm

3.3. Pixel labeling using level sets

Subsequently we introduce a level set algorithm for labeling according to the extracted features. The fast marching level-set algorithm introduced by Sethian [7] computes a constructive solution to the stationary level set equation

$$|\nabla T(x,y)| = \frac{1}{v(x,y)} \tag{7}$$

where $v(x,y)$ corresponds to the velocity of the moving front, while $T(x,y)$ is a map of crossing times. A thorough presentation of the level set method is given in [8], and a review of the fast marching algorithm appears in [9].

The proposed algorithm is a variant of the fast marching algorithm, which, in addition to the properties of the original, is able to cope with multiple classes (or labels). The algorithm described below assumes the existence of an initialization for $T(x,y)$, specifically its zero level set. There are three possible states for each pixel. An “alive” pixel represents a fixated arrival time value. A “trial” pixel constitutes a candidacy for a specific label with an arrival time value subject to change. “Far away” pixels have not yet been processed. When no more trial pixels exist the alive pixel with the smallest arrival time is used to label each pixel.

The algorithm is supplied with a label map partially filled with decisions. A map with pointers to linked lists of trial pixels is also maintained. Those lists are initially empty except for the sites being neighbors to initial decisions. For those sites a trial pixel is added to the corresponding list for each different label of neighboring decisions and an initial arrival time is assigned. All trial pixels are contained in a common priority queue.

Until no more trial pixels exist, the trial pixel with the smallest arrival time is selected and turned alive. If no other alive pixel exists for this site, its label is copied to the final label map. For all non-alive neighbors of this site a trial pixel of the same label is added, if it does not already exist, in the corresponding trial lists. Finally all neighboring trial pixels of the same label update their arrival times according to the new data.

An initial map of labeled sites is obtained using statistical tests. These tests classify points with high confidence. The probability of classification error is set to a small value. The multi-label fast marching level set algorithm is then applied for all sets of points initially labeled. The contour of each region propagates according to a motion field which depends on the label and on the distance of the considered point from the candidate label. The exact propagation velocity for a given label is

$$v_j(m,n) = \frac{\Pr(j)}{\sum_{l=1}^{L} \Pr(l) e^{d_j(m,n) - d_l(m,n)}} \tag{8}$$

The expression of the propagation speed is motivated by the maximum *a posteriori* probability criterion. The candidate label is propagated according to the *a posteriori* probability, which is expressed using the likelihood function of each label.

In Fig. 2 the segmentation result on the *zebra* image is presented. Only the luminance histograms are used for the segmentation. In Fig. 3 the segmentation result on the natural scene of *GrassPlants* (MIT Media Lab Vistex data set) is given. In this case only the histograms of the chromaticity components (a,b) are used. In Fig. 4 results of combined use of both texture and color in the *SeaStones* image (Fig. 1) are presented.

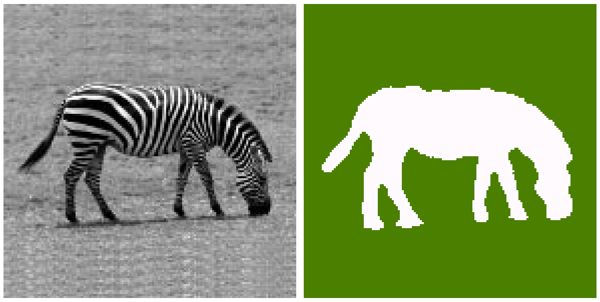

Figure 2. Segmentation of the *zebra* image

Figure 3. Segmentation of *GrassPlants*

4 Conclusion

The problem of image segmentation using color and texture is addressed. Two new segmentation algorithms are proposed using the extracted features (DWF and 2-D chromaticities histograms of *Lab*). In the first stage the parameters of the image patterns are automatically extracted. This procedure starts by identifying homogeneous blocks in color and texture. The different color-texture parameters are estimated after applying a hierarchical clustering procedure in the remaining blocks. The proposed scheme assumes that only the number of different patterns is known. In the future we will study techniques for estimating the number of patterns, in which case the segmentation process will be completely unsupervised. Very good segmentation results are obtained, either after median filtering and applying a deterministic relaxation algorithm, or by propagating initial label decisions using a fast marching algorithm.

Acknowledgments

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References

[1] J. Besag. On the statistical analysis of dirty images. *Journal of Royal Statistics Society*, 48:259–302, 1986.

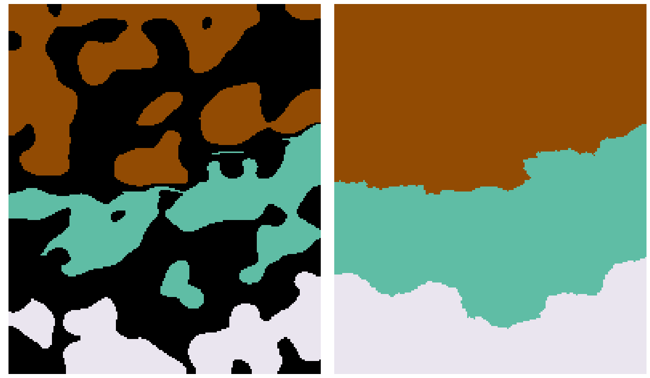

Figure 4. Initial map and final result of level set segmentation in the *SeaStones* image

[2] P. Chou and C. Brown. The theory and practice of Bayesian image labeling. *International Journal of Computer Vision*, 4:185–210, 1990.

[3] R. Duda and P. Hart. *Pattern Classification and Scene Analysis*. New York: J. Wiley & Sons, 1973.

[4] S. Geman and D. Geman. Stochastic relaxation, gibbs distributions, and the Bayesian restoration of images. *IEEE Trans. Patt. Anal. Machine Intell.*, 6:721–741, 1984.

[5] S. Liapis, N. Alvertos, and G. Tziritas. Unsupervised texture segmentation using discrete wavelet frames. *European Signal Processing Conference*, IV:2529–2532, 1998.

[6] S. Belongie, C. Carson, H. Greenspan, and J. Malik. Color- and texture-based image segmentation using EM and its application to content based image retrieval. In *Int. Conf. Comp. Vis.*, 1998.

[7] J. Sethian. A marching level set method for monotonically advancing fronts. *Proc. Nat. Acad. Sci.*, 93:1591–1595, 1996.

[8] J. Sethian. Theory, algorithms, and applications of level set methods for propagating interfaces. *Acta Numerica*, pages 309–395, 1996.

[9] J. Sethian. Fast marching methods. *SIAM Review*, 41:199–235, 1999.

[10] M. Unser. Texture classification and segmentation using wavelet frames. *IEEE Trans. on Image Processing*, 4:1549–1560, November 1995.