Unsupervised Natural Image Segmentation Using Mean Histogram Features

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Abstract—A new histogram feature based natural image segmentation algorithm has been proposed. The proposed scheme uses histogram based new color texture extraction method which inherently combines color texture features rather than explicitly extracting it. A non parametric Bayesean clustering is employed to make the segmentation framework fully unsupervised where no a priori knowledge about the number and types of regions are required. The performance of the proposed method have been demonstrated by various experiments using images of natural scenes. The experimental results indicates that superior segmentation results can be obtained through the proposed unsupervised natural image segmentation algorithm.

Index Terms—image segmentation, naturale scene, color texture feature, mean histogram, non parametric Bayesian clustering

I. INTRODUCTION

Segmentation of natural images is a challenging task as the images are of complex composition of both color and texture regions. A difficult problem for segmentation of natural images arises from the fact that, those images contain more or less pure textures and the texture properties are not well defined [1]. Also natural images exhibit significant inhomogeneities in color and texture.

There have been many methods proposed for color segmentation and texture segmentation, but only a few number for colored texture segmentation. Although significant progress has been made in texture segmentation and color segmentation separately, the area of combined color and texture segmentation remains open and active [1].

Recently, some methods have been proposed for color textured image segmentation. In [2], the color and texture features were extracted separately and combined for color texture segmentation using Kolmogorov-Smirnov test. Chen et al. [3] proposed a segmentation method using the distributions of color and local edge patterns which is used to derive a homogeneity measure for color texture segmentation. Jain and Healey [4] introduced a method for color texture classification based on unichrome features computed from the three spectral bands independently and opponent color features that utilize the spatial correlation between spectral bands. It was found that the inclusion of color increases the classification results without significantly complicating the feature extraction algorithms. Pietiekainen et al. [5] presented a color texture classification based on separate processing of color and pattern information. From the classification results it was concluded that color and texture have complementary roles. Some of the other recent work includes JSEG [6], stochastic model-based approaches [7], [8], [9] watershed techniques [10], edge flow techniques [11], and normalized cuts [12].

More recently, Tao and Jin [13] proposed a color image segmentation technique incorporating the advantages of the mean shift segmentation and the normalized cut partitioning methods. They preprocess the image using mean shift algorithm and then apply normalized cut method to perform globally optimized clustering. Ilea and Whelan [14] proposed a segmentation algorithm where color and texture features are adaptively evaluated by a clustering strategy. They used SOM to extract the dominant colors and estimate the optimal number of clusters in the image. Finally they integrate the color and Gabor texture features in a compound mathematical descriptor with the aim of identifying the homogenous regions in the image. Krinidis and Pitas [15] presented an energy function based approach for the segmentation of color textured images. In their paper they employ a color quantization scheme to decrease the number of colors in the image initially. Then, they use an energy function as a criterion for a region growing algorithm. The final segmentation of the image is derived by a region merge approach.

The use of multiple types of features in segmentation can be exploited to take full advantage of the strengths of each feature type. Ideally, one would like to select complementary types of features that are not highly correlated and, when combined, can improve the final segmentation result [16]. One way of combining two types of features is to concatenate the feature vectors and perform the classification step on the augmented feature set. This method has been used for combining texture and color features as well as texture features of different types [16]. But in doing so normalizing and proper weighting is required since in most cases the number of parameters in the different feature sets is not equal. In addition, by concatenating all the features into a single vector, the segmentation result is based on a global clustering criterion, even though it may be more suitable to constrain clustering of certain features to a local neighborhood.

In this study, we present a new framework for natural image segmentation which uses integrated color and the texture features along with an unsupervised segmentation...
algorithm. Rather than extracting color and texture features separately, we utilize a new inherent color texture feature for segmentation of images of natural scenes which in our opinion is effective for such case. From color and the color texture features, mean histograms are calculated. A fully unsupervised multichannel histogram clustering method is employed for initial segmentation. Final segmentation is obtained from region merging. The proposed segmentation framework is depicted in Figure 1.

This paper is organized as follows. Section 2 gives proposed feature extraction method. Section 3 discusses the image segmentation algorithm using the proposed features. In Section 4, experimental results and performance of the proposed method are discussed. Finally, conclusions are given in Section 5.

II. PROPOSED FEATURE EXTRACTION METHOD

A. Color Space

Color is an important feature for image representation which is widely used in many applications. It is invariant with respect to image scaling, translation, and rotation. The key items in color feature extraction consist of color space, color quantization, and the kind of similarity measurements. The RGB color format is the most common color format for digital images. The primary reason for this is because it retains compatibility with computer displays. However, the RGB space has the major drawback in that it is not perceptually uniform. Because of this, uniform quantization of RGB space gives perceptually redundant bins and perceptual holes in the color space. Furthermore, ordinary distance functions defined in RGB space will be unsatisfactory because perceptual distance is a function of position in RGB space. Other color spaces, such as CIE-LAB, CIE-LUV and Munsell offer improved perceptual uniformity [17]. In general they represent with equal emphasis the three color variants that characterize color: hue, lightness, and saturation. This separation is attractive because color image processing performed independently on the color channels does not introduce false colors. Unlike the RGB color models, Lab color is designed to approximate human vision. It aspires to perceptual uniformity, and its L component closely matches human perception of lightness. It can thus be used to make accurate color balance corrections by modifying output curves in the a and b components, or to adjust the lightness contrast using the L component.

B. Color Features

Though RGB color format is the most common color format for digital images but the RGB space is not perceptually uniform. As discussed earlier, CIE-LAB (Lab) and CIE-LUV offer improved perceptual uniformity. On the other hand, HSV color space is also compatible with human color perception. In our case, CIE-LAB and HSV color spaces both for extracting color feature. To extract color features, we construct histograms of square window centering around each pixel on an equidistant grid in each image plane using both Lab and HSV color spaces. A histogram represents the distribution of the number of pixels for an image. The color histogram represents the color content of an image which is robust to translation and rotation [18]. After obtaining the histogram features, mean histograms are calculated. We use $5 \times 5$ window size in extracting histograms for three image channels. A large window yields smooth segmentation but coarsen the resolution, on the other hand smaller window preserves detail in the segmentation map. In our experiments, we found that $5 \times 5$ window is a better tradeoff for the proposed segmentation framework.

C. Color Texture Features

In the literature, Gabor filters are mostly used to extract texture features for the segmentation. Gabor filters compute the textural characteristic by first transforming the image into the frequency domain and then dividing the domain into several frequency subbands. The distribution of energy in each of these subbands is used as the basis for distinguishing different textures. This approach to texture analysis is intuitively appealing because the dominant spatial-frequency components of different textures are different. Unfortunately, Gabor filters have the decisive drawback that they induce a lot of redundancy and thus lots of feature channels [19].
To overcome this problem Bigun et al. [20] used structure tensor in order to discriminate textures. However, the Gaussian smoothing used for the structure tensor dislocates the edges in feature space leading to inaccurate segmentation results. Rousson et al. [19] proposed a local structure tensor (LST) based textured image segmentation method that applies the geodesic active regions (GAR) model to a vector-valued image where the channels are the components of the LST. However, the advantages of extracting the texture features with the LST are partially lost because of the vector processing of that information. Garcia et el. [21] proposed an adaptive segmentation method that combines the LST with the image components into a common energy minimization framework. But the regularization constraints used in the minimization process prevents the segmentation from being completely accurate in the presence of sharp corners. Moreover, when multiple level sets are used, problems of vacuum and overlap appear and need to be solved by imposing additional constraints.

As natural images contain more or less pure textures and the texture properties are not well and they exhibit significant inhomogeneities in color and texture, we propose a new color texture feature extraction method based on higher order image statistics which defines texture regularity in neighborhood structures. The image statistics can be recovered through unsupervised learning as proposed in [22].

Here, image \( I \) is considered to be a random field \( X \) with a set of lattice points \( S \) where \( \{s\}_{s \in S} \) is the set of pixels in the image. A pixel neighborhood system \( N = \{N_s\}_{s \in S} \) for the set \( S \) is defined such that \( N_s \subseteq S \) and \( q \in N_s \) if and only if \( s \in N_q \) where \( N_s \) is called neighbors of \( s \). A random vector, \( Y(s) = \{X(s)\}_{s \in N_s} \) is defined corresponding to the set of intensities at the neighbors of pixel \( s \). Another random vector, \( Z(s) = (X(s), Y(s)) \) is defined to denote image regions, i.e., pixels combined with their neighborhoods.

In order to extract color texture feature, we employ an unsupervised, information-theoretic, adaptive filter (UINTA) [22] that improves the predictability of pixel intensities from their neighborhoods by decreasing their joint entropy \( h(X|Y = y) \), of the conditional PDF for each pixel-neighborhood pair, \( (X = x, Y = y) \) by manipulating the value of each center pixel \( x \). Entropy reduction reduces the randomness locally and thus produces homogenous intensity regions for different texture regions.

For this, in each iteration and for each image region, \( z^m \),

\[
\frac{\partial h(X|Y = y^m)}{\partial x^m} \tag{1}
\]

is computed. Then, image \( I^{m+1} \) is constructed using finite forward differences on the gradient descent, with intensities

\[
x^{m+1} = x^m - \lambda \frac{\partial h}{\partial x^m} \tag{2}
\]

where \( \lambda \) is the time step. A Parzen-window based non-parametric density estimation technique is used with an n-dimensional Gaussian kernel, \( G_n(z, \phi_n) \) for density estimation. Having no a priori information on the structure of the PDFs, an isotropic Gaussian is chosen, i.e., \( \phi_n = \sigma I_n \) where \( I_n \) is the \( n \times n \) identity matrix. Employing a data driven approach, the value of \( \sigma \) is chosen so that the joint entropy is minimized [22]. Assuming a stationery ergodic random field the multivariate Parzen-window estimate is

\[
P(Z = z(s)) \approx \frac{1}{|A_k|} \sum_{t_i \in A_k} G_n(z(s) - z(t_i), \phi_n), \tag{3}
\]

where the set \( A_k \) is a small subset of \( S \) chosen randomly, from a uniform PDF, for each \( s \). For our case, we stop pixel updating process after few iterations when \( \|I^{m+1} - I^m\|_2 < \delta \), a small threshold. We set time step \( \lambda = .3 \) in all of our experiments. For extracting color texture feature, filtering is performed for three Lab image channels. Again, for each feature image, we extract window features of size \( 5 \times 5 \) and the features are gaussian smoothed before making local histograms.

D. Mean Histogram Features

The final step in feature extraction process is the calculation of mean weighted histogram. As color and texture in a color textured image plays complementary roles [23], this integration will help improve the final...
segmentation result. If there are \( N \) feature histograms with \( C \) channels each, the channel wise weighted mean histogram, \( H_j \) can be calculated as

\[
H_j = \sum_{i=1}^{N} w_i h_{ij}
\]

where \( w_i \) is the weight assigned to each histogram. The mean histogram is composed of channel wise weighted mean histograms, \( H = \{H_j\}_{j=1..C} \).

The proposed color texture features are extracted using local window and they have inherent similarity. For this, we can put equal weights to each features, i.e., \( w_i = 1/N \).

III. SEGMENTATION

A. Clustering using Dirichlet Process Mixture Model

The long standing problem in all clustering procedures, including mixture models, is the problem of determining the number of clusters. One way to handle this problem is to define mixture distributions with a countably infinite number of components. This models can be implemented by employing a Dirichlet process prior for the mixing proportions, and various Markov chain Monte Carlo sampling methods for fitting Dirichlet process mixture models have already been proposed in the literature. We, therefore, select a nonparametric Bayesian approach based on Dirichlet process mixture models (DPMM) [24] [25] which can provide a framework for Bayesian clustering with an unknown number of groups.

Let \( Y = (y_1, ..., y_n) \) be \( p \)-dimensional observations arising from a mixture of distributions \( f(\cdot | \theta_i) \). The model parameter specific to individual \( i, \theta_i \), are assumed to be independent draws from some distribution \( G \), which in turn follows a Dirichlet process (DP) \( DP(\alpha G_0) \) where \( G_0 \) is the base distribution and \( \alpha \) is the concentration parameter. Then, Bayesian hierarchical model with a DP prior can be written as follows:

\[
y_i \sim f(\cdot | \theta_i),
\]

\[
\theta_i \sim G,
\]

\[
G \sim DP(\alpha G_0).
\]

From the definition above, a DP is considered as a distribution function over all possible distributions. Moreover, the underlying random probability distribution \( G \) is discrete with probability one, so that the support of \( G \) consists of a countably infinite set of atoms, drawn independently from \( G_0 \).

The representation via the Pólya urn scheme, described by Blackwell and MacQueen [26], shows the cluster formation and sample allocation. In (5), when \( G \) is integrated out over its prior distribution, the conditional distribution of \( \theta_i \) following Pólya urn scheme may be represented as:

\[
p_i(\theta_i | \theta_{-i}) = \frac{\alpha}{\alpha + n - 1} G_0(\theta_i) + \frac{1}{\alpha + n - 1} \sum_{j=1,j \neq i}^{n} \delta_{\theta_j}(\theta_i)
\]

where \( \theta_{-i} \) represents the parameter set \( \{\theta_1, ..., \theta_{i-1}, \theta_{i+1}, ..., \theta_n\} \) with \( \theta_i \) removed and \( \delta \) represents a Dirac measure concentrated at \( \theta \).

As can be seen in equation (6) that the Dirichlet process exhibits a clustering property as a result of the discreteness property of the random measure \( G \). It is obvious that a \( \theta_i \) has its own new value randomly selected from \( G_0 \) with a probability proportional to \( \alpha \), and is assigned to one of the existing values \( \theta_j \)'s, \( j \neq i \), with a probability proportional to number of same values previously sampled. At the end, all sampled \( \theta_i, i = 1, ..., n \) form \( K \) clusters with \( K \leq n \), and each cluster \( k \in \{1, ..., K\} \) has its distinct characteristic \( \phi_k, k = 1, ..., K \) such that \( \theta_i = \phi_k \) for a subset of index \( i \) in cluster \( k \). In other words, given \( K \), the \( \theta_1, ..., \theta_n \) are selected from the set \( \phi = (\phi_1, ..., \phi_K) \) according to a multinomial distribution.

If we denote the number of samples in group \( k \) by \( n_k \), the distribution of (6) may be rewritten as a sum over clusters rather than individual samples:

\[
p_i(\theta_i | \theta_{-i}) = \frac{\alpha}{\alpha + n - 1} G_0(\theta_i) + \sum_{j=1}^{K} \frac{n_j - i}{\alpha + n - 1} \delta_{\theta_j}(\theta_i)
\]

where \( n_j^{-i} \) represents the number of elements in cluster \( j \) when observation \( i \) is removed.

Posterior expectations for the DP mixture model (5) can be estimated employing Gibbs sampler. In [27] Bush and MacEachern proposed a Gibbs sampler in order to improve convergence of the Markov chain to the posterior distribution by using indicator variables \( s_i \). The variable \( s_i \) indicates which latent class is associated with observation \( y_i \). Let \( s = s_1, ..., s_n \) denote the vector of indicator variables defined by \( s_i = j \) if \( \theta_i = \phi_j, i = 1, ..., n \).

To sample a cluster assignment \( s_i \) given a current set of parameters \( \theta_1, ..., \theta_n \) and the datum \( y_i \), the posterior probability of occurrence for each class is given by

\[
p_s(\theta_i | \theta_{-j}, s_{-i}, y) \propto \sum_{k=1}^{K} q_{ij} + q_{00},
\]

where \( n_{-i}^{-} \) represents the number of elements in cluster \( j \) when observation \( i \) is removed and the chances \( q_{ij}, q_{00} \) are given by

\[
q_{ij} = n_{ij}^{-1} f(y_i | \phi_j), q_{00} = \alpha \int f(y_i | \theta_i) G_0(\theta_i) d\theta_i.
\]

This chances can be transformed into cluster probabilities \( q_{ij}, l = 0, ..., K \) by normalization.

The sampling rule expressed by (9) is simple. A cluster assignment \( s_i \) is sampled by sampling from the finite probability distribution defined by the vector \( q_{00}, ..., q_{0K} \). In the second step, new values for the cluster parameters \( \phi_k \) are chosen by sampling from the class posterior, i.e.,
the posterior based on all data values currently assigned to the given class:

\[ \phi_k \sim G_0(\phi_k) \prod_{i \mid s_i = k} f(y_i | \phi_k). \]  

The above DPMM model can be adapted for histogram clustering following [28]. In the histogram clustering model we also assume that \( f \) is a multinomial distribution, \( G_0 \) a Dirichlet distribution and the observed data \( y_i \) are the histograms with \( B \) bins, \( H_i = (h_{i1}, ..., h_{iB}) \). The density

\[ f(H_i | \theta_i) = 1 / A_M(H_i) \prod_{j=1}^{B} \theta_{ij}^{h_{ij}} \]  

describes the multinomial distribution of \( H_i \) given bin probabilities, \( \theta_i \). The normalization function \( A_M(H_i) \) does not depend on the value of \( \theta_i \). Each vector \( \theta_i \) is assumed to be drawn from the respective conjugate prior, a Dirichlet distribution

\[ G_0(\theta_i | \beta, \pi) = 1 / A_D(\beta, \pi) \prod_{j=1}^{B} \theta_{ij}^{\beta_j - 1} \]  

where \( \beta \) is a positive scalar and \( \pi \) is a \( B \)-dimensional probability vector and \( A_D(\beta, \pi) = \prod_{j=1}^{B} \Gamma(\beta_j) / \Gamma(\beta) \). Due to the conjugacy of \( f \) and \( G_0 \), the integral required for the computation of \( \hat{q}_0 \) may be solved analytically. Incorporating smoothness constraints with cost function

\[ U(\theta_i | \theta_{-i}) = -\eta \sum_{j \in N_i} \delta_{\theta_i, \theta_j} \]  

where, \( \delta \) is a Kroneker’s symbol, \( N_i \) is set of neighborhood pixel indices of pixel \( i \), cluster proportions in equation (9) can be assigned as [28]:

\[ q_{ij} = n_j^{-1} \exp(-\eta \sum_{j \in N_i} \delta_{\theta_i, \theta_j}) \prod_{k=1}^{B} \theta_{ik}^{h_{ik}}, \]

\[ q_{i0} = \frac{A_D(\beta \pi + H_i)}{A_D(\beta \pi)}. \]  

B. Region merging

The final stage of our segmentation algorithm is to merge regions in order to enforce that the resulting segmentation respects spatial continuity and consists of only connected segments. To ensure this condition to be reflected in the final segmentation result, we impose constraints that two regions \( R_i \) and \( R_j \) can be merged together only if they are spatially adjacent in the 2D image and any of the regions is smaller than a pre specified size threshold. After the completion of the merging process final segmentation result is obtained.

IV. EXPERIMENTAL RESULTS

To evaluate the performance of the proposed segmentation framework, a large number of experiments were carried out.

In order to illustrate the validity and performance of the proposed scheme, we compare the results of our approach with the image segmentation results achieved using the well known JSEG method described in [6] and also with the ones described in [29] which has been extended in [30]. The JSEG results were obtained from applying the images to the programs made available by the JSEG authors online [31] which we think are most relevant to compare with those of our algorithm. JSEG involves three parameters namely the color quantization threshold, the scale and the merge threshold which are to be set by the user. Color quantization threshold determines the minimum distance between two quantized colors and it ranges from 0 to 600. A large threshold yields less number of quantized colors. On the other hand, a small threshold usually results in large number of quantized colors, which will degrade the performance of homogeneity detection. Region merge threshold specify values from 0.0 to 0.7. The default value is 0.4. If it is needed to segment a small object in a large-sized image, more number of scales are required. To have a coarse segmentation, 1 scale is used. In this study we set the values 255, 1.0, and 0.4, respectively as suggested by the authors.

In [29], an image is over segmented using low level features. Next the segments are merged using texture features in such a way that the overall coding length of
Figure 4. Segmentation results of natural images. First column represents sample images. The second column shows segmentation results by JSEG. The third column shows segmentation results generated by the algorithm proposed in [30]. Fourth column shows segmentation result by the proposed algorithm.
the feature vectors is minimized. The idea has recently been extended in \cite{30} using boundary encoding. The segmentation results shown in column 3 of Figure 4 are obtained through this algorithm which are available online \cite{30}.

For the proposed algorithm, in histogram clustering, we used Dirichlet distribution with base measure, $G_0 = G_0(|\beta\pi)$. We set vector $\pi = (1/B, ..., 1/B)$ and $\beta = 2T$ where $T$ is the total number of data points in a local window to make histograms and $B$ is total number of bins in the histogram. Sampling were performed parallelley for 3 individual channels. We put equal weights in constructing final color texture features. The minimum region size threshold was set to such values so that the final segmented regions obtained become roughly compatible with original image regions for better qualitative comparison.

We have applied our technique to Berkeley segmentation database \cite{33} which consists of 300 natural images along with their segmentation results, each of which has been hand segmented by multiple human subjects. These human segmented images provide the ground truth boundaries for quantitative evaluation of the performance of our method, JSEG and the method proposed in \cite{30}.

![Figure 5. Some complex natural image segmentation results. Top most row shows sample images. Second row shows the segmentation results by the proposed segmentation framework when using only color features. Third row shows segmentation results using JSEG. Fourth row shows segmentation results using \cite{30}. Fifth row shows segmentation result by proposed segmentation framework using color texture features.](image)

<table>
<thead>
<tr>
<th>Method</th>
<th>PR index</th>
<th>VOI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Method in \cite{30}</td>
<td>0.80</td>
<td>1.76</td>
</tr>
<tr>
<td>JSEG</td>
<td>0.7743</td>
<td>2.3148</td>
</tr>
<tr>
<td>Proposed</td>
<td>0.7981</td>
<td>1.8227</td>
</tr>
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</table>

We present the segmentation steps of the proposed algorithm for natural scenes in Figure 3. Two natural sample images collected from Berkely segmentation database \cite{33} are shown in Figure 3a and in Figure 3e. Initial segmentation maps are shown in Figure 3b and Figure 3f respectively. Final segmentation maps are shown in Figure 3c and Figure 3g respectively. The final segmentation results are shown in Figure 3d and Figure 3h respectively.

For quantitative measurements we calculated the Probabilistic Rand index (PR) and Variation of Information (VOI) metric using for natural images from Berkeley \cite{33} database using proposed method and JSEG. Rao et al. \cite{30} did the same experiment on the same database using their proposed method which they call Texture and Boundary Encoding based Segmentation (TBES). The PR index measures the agreement between the segmented result and
the manually generated ground-truths and takes values in the range [0, 1]. A higher PR value indicates a better match between the segmented result and the ground-truth data. On the other hand VoI defines the distance between two segmentations as the average conditional entropy of one segmentation given the other, and thus roughly measures the amount of randomness in one segmentation which cannot be explained by the other. VoI ranges between [0,∞), and lower is better. As we have multiple ground-truth segmentations, to compute a given metric for a test segmentation, we simply average the results of the metric between the test segmentation and each ground-truth segmentation similarly done in [30].

Table I depicts the PR index and VoI metric obtained from the segmented results of the proposed method, JSEG and the performance reported in [30]. The higher PR value achieved by the the proposed algorithm suggests that it can perform perceptually better segmentation than JSEG. It also suggests that the performance of the proposed algorithm is competitive with that of the algorithm proposed in [30]. The value of VoI for the proposed algorithm is also comparable to the algorithm with [30]. It is to be noted that, the proposed algorithm uses mean histogram features. Instead of equal weights, if the weights of color and color texture features for the proposed segmentation framework are chosen in accordance with image characteristics, better segmentation can be achieved.

To demonstrate the superiority of the proposed method, set of sample segmentation results are presented in Figure 4. These images are composed of regions with fuzzy boarders, inhomogeneous texture characteristics and low color contrast. Yet, the experimental results in Figure 4 and figures in Table I indicate that the proposed algorithm is able to produce consistent segmentation results in producing perceptually uniform regions. The results also indicate that the proposed algorithm has better ability than the JSEG algorithm in handling the local inhomogeneities in texture and color because of using mean histogram features. Another set of segmentation results of some complex natural images obtained by JSEG, method described in [30] and the proposed algorithm are shown in Figure 5. Here we also include the segmentation results through proposed segmentation framework using only color features.

From Figure 4 and Figure 5, it is noticeable that the JSEG and algorithm in [30] perform well in the identification of the image regions defined by similar color texture properties, but they fail to determine accurately the object borders between the regions that are characterized by low color contrast. The segmentation results also reveal that the proposed segmentation framework performs better when it utilizes color texture features rather than color features only. Almost in all cases the proposed algorithm achieved far superior segmentation results.

V. Conclusions

In this paper, we presented a new framework for natural image segmentation that is based on novel color texture features. To solve the natural image segmentation problem, the proposed method unifies color and texture features in true sense rather than simply extend gray-level texture analysis to color images, or analyze only spatial interaction of colors in a neighborhood to extract texture features. The proposed segmentation framework is fully unsupervised and no a priori knowledge about the number and types of color and texture regions are required. The performance of the developed segmentation algorithm has been evaluated on a publicly available natural image database and the superior of the proposed algorithm has been confirmed both qualitatively and quantitatively.

REFERENCES


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