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A Novel Image Segmentation based on a Combination of Colour and Texture Features

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Abstract
This paper aimed at segmentation of natural images, in which the color and texture of each segment does not typically exhibit uniform statistical characteristics due to effect of lighting, perspective, scale changes, etc. 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. The proposed approach is based on two types of spatially adaptive low-level features. The first describes a spatially adaptive dominant color, obtained using Adaptive Clustering Algorithm (ACA), and second is the spatial characteristic of the grayscale component of the texture, obtained from the detail coefficient of Complex Wavelet Decomposition (CWD). Together, they provide a simple and effective characterization of texture that the proposed algorithm uses to obtain robust and, at the same time, accurate and precise segmentations. Initially, image pixels are classified into smooth and non-smooth or texture pixels. The smooth pixels are segmented using the morphological watershed algorithm. The non-smooth pixels are segmented by two steps. First step is the crude segmentation by Multi-grid Region Growing algorithm and the second step is the iterative edge refinement. The resulting segmentations convey semantic information that can be used for content-based retrieval. The performance of the proposed algorithms is numerically evaluated, compared with other algorithms and found to be the best.

Keywords: *Texture image segmentation, complex wavelet, texture, watershed, region growing.*

1. Introduction
Image segmentation is useful in many applications for identifying regions of interest in a scene or annotating the data. The MPEG-4 standard needs segmentation for object-based video coding. Natural scenes are rich in color and texture. Many texture segmentation algorithms require the estimation of texture model parameters. Parameter estimation is a difficult problem and often requires a good homogeneous region for robust estimation. Another challenging aspect of image segmentation is the extraction of perceptually relevant information. Since humans are the ultimate users of most content-based image retrieval (CBIR) systems, it is important to obtain segmentations that can be used to organize image contents semantically, according to categories that are meaningful to humans. This requires the extraction of low-level image features that can be correlated with high-level image semantics. This is a very challenging problem. However, rather than trying to obtain a complete and detailed description of every object in the scene, it may be sufficient to isolate certain regions of perceptual significance (such as "sky," "water," "mountains," etc.) that can be used to correctly classify an image into a given category, such as "natural," "man-made," "outdoor," etc.

There are two main goals in this work. The first goal is to develop segmentation algorithms for images of natural scenes, in which color and texture typically do not exhibit uniform statistical characteristics. The second one is to incorporate knowledge of human perception in the design of underlying feature extraction algorithms.

Some of the recent works in colour image segmentation algorithms [19-20] include stochastic model-based approaches, morphological watershed-based region growing, energy diffusion, adaptive clustering [11] and graph partitioning [3,6,14,16,18]. Similarly algorithms for texture image segmentation include texture watershed segmentation [5], region growing for texture image [1].

An image segmentation algorithm is presented, based on spatially adaptive texture features [2]. As illustrated in Fig. 1, two types of features are developed, one describes the local color composition and the other is the spatial characteristics of the greyscale component of the texture. These features are first developed independently, and then combined to obtain an overall segmentation. Here adaptive clustering algorithm [2] is to segment smooth pixels. But it is not suitable for unsupervised segmentation. We proposed watershed segmentation to segment the smooth pixels and the extraction of texture

feature is by complex wavelet decomposition (6 detailed sub bands) as an alternative to the steerable filters [2].
The proposed approach uses ACA as a building block. It separates the image into non-textured and textured areas, and combines the color composition and spatial texture features to consolidate textured areas into regions. This is done in two steps. The first relies on a multigrid region growing algorithm to obtain a *crude* segmentation. The segmentation is crude due to the fact that the estimation of the spatial and color composition texture features requires a finite window. The second step uses an elaborate border refinement procedure to obtain accurate and precise border localization by appropriately combining the texture features with the underlying ACA segmentation.

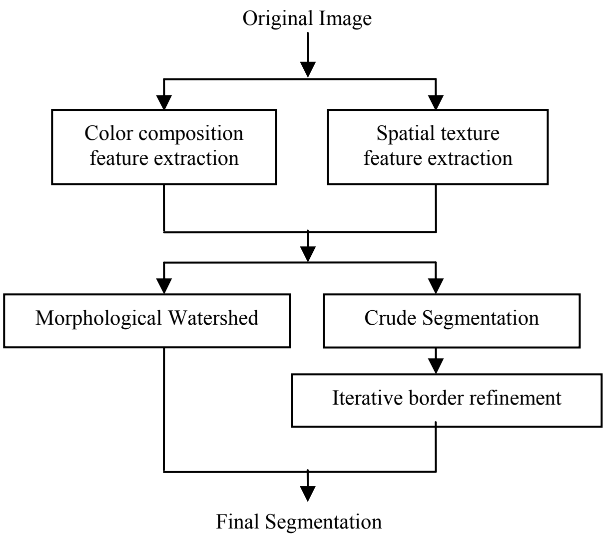


Figure. 1 Overview of algorithm

For segmenting the non-texture region morphological gradient watershed is used. The gradient is computed using Gaussian derivatives. The main drawback of watershed is the over segmentation. In order to avoid this over segmentation a pre processing step called H-minima transform, which suppresses the local-minima due to noise, is applied.
Several color representations are currently in use in color image processing. The most common is the RGB space where colors are represented by their red, green and blue components in an orthogonal Cartesian space. The proposed method is based on this RGB representation of color image.
The colour and texture feature extraction methods are explained in Section (2) and (3) respectively. Section (4) explains the segmentation of smooth regions using watershed. Section (5) describes the segmentation of non-smooth regions using multigrid region growing and edge refinement. The results, comparisons to other approaches and their performance evaluation results are given in Section (6), followed by conclusion in section (7).

2. Color feature

Our goal is to produce a system that performs in accordance with human perception, hence it needs a representation (color space) based on human color matching. An important characteristic of human color perception is that the human eye cannot simultaneously perceive a large number of colors [10], even though under appropriate adaptation, it can distinguish more than two million colors. A small set of color categories provides a very efficient representation, and more importantly, makes it easier to capture invariant properties in object appearance. The colors, in this small set, are called dominant colors.
The idea of using a compact color representation in terms of dominant colors for image analysis was introduced by Ma *et al.* [8]. Color clustering is performed on whole image to obtain its representative colors. After clustering, only a small number of colors remain and the percentages of these colors are calculated. Each representative color and its corresponding percentage form a pair of attributes that describe the color characteristics in an image region. The dominant color descriptor is defined to be

$$f_s = \{ (c_i, p_i), i = 1,\ldots,N, p_i \in [0,1]\} \quad (1)$$

where each of the dominant colors, c_i, is a three-dimensional (3-D) vector in *RGB* space, and p_i are the corresponding percentages.
Spatially adaptive dominant colors can be obtained using the ACA [11]. The local intensity functions of the ACA can be used as spatially adaptive dominant colors. The ACA is an iterative algorithm that can be regarded as a generalization of the k-means clustering algorithm in two respects: it is adaptive and includes spatial constraints. It segments the image into classes. Each class is characterized by a spatially varying characteristic function that replaces the spatially fixed cluster centre of the k-means algorithm. In ACA alternates between estimating the distribution of regions x and the intensity functions μ^i_s. Note that, for a given ACA segmentation, the color feature vectors can be computed using a different window size, by averaging the colors of each class in the window and computing the percentage of pixels in each class.

$$f_s(x, y, N_{x,y}) = \{ (c_i, p_i), i = 1,\ldots,M, p_i \in [0,1]\} \quad (2)$$

where, $N_{x,y}$ are the neighbour pixels for the pixel located at (x, y).
Based on human perception, the color composition of two images (or image segments) will be similar if the colors are similar and the total areas that each color occupies are similar. Various suboptimal solutions have been proposed. Mojsilovic *et al.* [8] proposed the OCCD, which finds the optimal mapping between the dominant colors of two images and, thus, provides a better similarity measure. The OCCD, which is closely related to the *earth mover's* distance, requires more computation. However, since the primarily interest is in comparing image segments that contain only a few colors (at most four), the additional overhead for the OCCD is reasonable.

3. Texture feature

The greyscale component of the image is used to derive the spatial texture features, which are then combined with the color composition features to obtain an intermediate crude segmentation. Like many of the existing algorithms for texture analysis and synthesis, this algorithm is based on multi-scale frequency decomposition. Examples of such decompositions are the Cortex transforms [17], the Gabor transforms [12], the steerable pyramid decomposition [4], Complex wavelet decomposition [7] and the discrete wavelet transform (DWT), which can be regarded as a crude approximation of the cortex transform. Here, spatial texture feature extraction is based on complex wavelet decomposition, which can be designed to produce six different orientation bands.

The Complex Wavelet Transform (CWT) has the following properties,

- Approximate shift invariance
- Good directional selectivity in 2-dimensions (2-D) with Gabor-like filters

The magnitude of the coefficients of each complex subband can be used to characterize the texture content. This is because the basis functions from each subband (very closely) resemble Gabor filters. The detail coefficients of the dual-tree complex wavelet transform is used to process texture. The Output of the Complex wavelet decomposition has six detail subbands oriented to ± 75°,± 45° and ± 15° respectively and an approximation sub band.

The spatial texture feature extraction consists of two steps. First, classify pixels into smooth and non-smooth categories. Then, further classify non-smooth pixels into the remaining categories. Let $s_0(x, y)$, $s_1(x, y)$, $s_2(x, y)$, $s_3(x, y)$, $s_4(x, y)$ and $s_5(x, y)$ represent the magnitude of complex sub band coefficient at location that corresponds to the horizontal (+15^o), horizontal (-15^o), diagonal with positive slope (+45^o), vertical (+75^o), vertical (-75^o),and diagonal with negative slope (-45^o) directions, respectively. $s_{max}(x, y)$ is used to denote the maximum (in absolute value) of the six coefficients at location (x, y), and i to denote the sub band index that corresponds to that maximum. A pixel will be classified as smooth if there is no substantial energy in any of the six orientation bands. A pixel (x, y) is classified as smooth if the median of $s_{max}(x', y')$ over a neighbourhood of (x, y) is below a threshold T_0. This threshold is determined using a two-level K-means algorithm that segments the image into smooth and non-smooth regions. The next step is to classify the pixels in the non-smooth regions, according to the dominant orientation at that location.

The maximum of the six sub band coefficients, $s_i(x, y)$, is used to determines the orientation of the texture at each image point. The texture classification is based on the local histogram of these indices. A median type of operation is necessary for boosting the response to texture within uniform regions and suppressing the response due to textures associated with transitions between regions. This is done as follows. Compute the percentage for each value (orientation) of the index $s_i(x', y')$ in the neighbourhood of (x, y). Only the non-smooth pixels within the neighbourhood are considered. If the maximum of the percentages is higher than a threshold T_1 and the difference between the first and second maxima is greater than a threshold T_2, then there is a dominant orientation in the window and the pixel is classified accordingly. Otherwise, there is no dominant orientation, and the pixel is classified as complex. The first threshold ensures the existence of a dominant orientation and the second ensures its uniqueness. The values for these thresholds are 25% and 10% respectively. The window size for the median operation is 23 x 23.

The following distance function is used to find the similarity between the spatial texture features f^1_t and f^2_t.

$$D(f_t^1, f_t^2) = \begin{cases} 0 & \text{if } f_t^1 = f_t^2 \\ t_{i,j}, & \text{if } f_t^1 = i \neq f_t^2 = j \end{cases} \quad (3)$$

where, $t_{i,j}$ is the threshold depends on the combination of texture classes (smooth, +15, -15, +75, -75, +45, -45 and complex). Here, two different values are assumed for $t_{i,j}$, one for within non-smooth texture classes and the other for between smooth and non-smooth classes. The values are 0.5 and 1. This metric will be used in combination with the color metric to determine the overall similarity between two texture (color composition and spatial texture) feature vectors.

4. Segmentation of Smooth Region

The smooth and non-smooth regions are considered separately for segmentation. The ACA was developed only for images with smooth regions. But it has two main drawbacks. First, it needs some post processing like region merging. Second, it needs to specify the number of different clusters at the beginning of the algorithm, manually. Hence this algorithm is not suitable for unsupervised segmentation. In this proposed algorithm, Morphological Watershed algorithm an unsupervised segmentation algorithm is used.

The initial stage of gradient watershed segmentation is to produce a gradient from the original image. Since, RGB color plane is used in this work, the three different gradients for the three color planes have to be calculate, individually. The Gaussian derivative function is adapted as a gradient operator. The gradient magnitude, $|G(x,y)|$ of each sub band, is given by

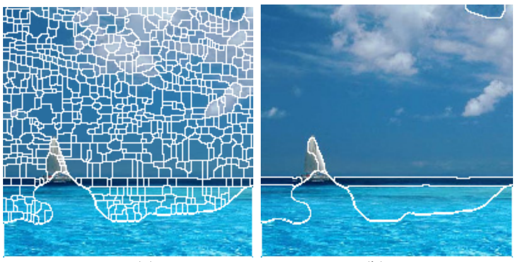
$$G(x,y) = \sqrt{(I(x,y) * G'_x)^2 + (I(x,y) * G'_y)^2} \approx |\nabla I(x,y)| \quad (4)$$

where, G'_x and G'_y are the Gaussian partial derivative filters in the x and y directions and * denotes convolution. I(x, y) is the intensity value at location (x, y). After getting the three gradient matrices, they have to be combined, to get the single gradient at each pixel. Let G_r, G_g and G_b are the gradients of the red, green and blue color planes respectively. They are combined using equation (5) to get the final gradient FG.

$$FG = [G^2_r + G^2_g + G^2_b]^{1/2} \quad (5)$$

This final gradient is taken as the input to the watershed. The main drawback of the watershed transform is the over segmentation. Ideally, each (perceptual) region of the image would have a single corresponding local minimum in the gradient function. However, noise and other small structures in the image function cause fluctuations in the gradient surface, resulting in the presence of many local minima. Each of these will be segmented as a separate region by the watershed process. The widely used solution is to use a marker-based watershed, transposing the problem to that of marker selection. Instead, the current method uses a region-depth criterion to modify the gradient function. The proposed method may also be viewed as using an adaptive threshold to "clip" the gradient surface.

The implementation relies on the morphological *H-minima transform*, which modifies the gradient surface, suppressing shallow minima. This can be imagined as an immersion process, minima are filled with a specified depth of water and those that "overflow" are removed (think of it as "filled in"). The subsequent watershed segmentation, therefore, does not have a region at such locations. The effect of H-minima transformation in the segmentation is illustrated in Fig. 2. From this figure it is easy to conclude that the H-minima transform can reduces the over segmentation in watershed to a great extend.



(a) (b)

Figure. 2, Segmented outputs with and without H-minima transform (shown in color)
(a) Final output without H-minima transforms
(b) Final output with H-minima transforms

5. Segmentation of Non-Smooth Region

The proposed segmentation algorithm combines the color composition and spatial texture features to obtain segments of uniform texture. This is done in two steps. The first relies on a multigrid region growing algorithm to obtain a *crude* segmentation. The second step uses an elaborate border refinement procedure to obtain accurate and precise border localization by appropriately combining the texture features with the underlying ACA segmentation.

A. Multigrid Region Growing

The Multigrid Region Growing algorithm adapts to non-uniformity of the textures that are found in natural scenes, namely the intensity, color, and texture of a perceptually uniform region by estimating the color composition texture parameters over a hierarchy of window sizes that progressively decrease as the algorithm converges to the final segmentation.

The steps of the Multigrid Region Growing algorithm.

step1: Fix the window size and grid spacing equals to half the window size. Place the virtual grid on the image.

step2: Compute the color composition feature for the grid points with the window centred at the grid points, in non-texture regions. The non-smooth pixels and smooth pixels, which are neighbour to the non-smooth pixels, with in the window, are considered for finding the color feature.

step3: Compute the similarity between the current pixel and its neighbour pixels.

step4: Find the neighbour pixel, which has the minimum distance between them, and merge them.

step5: Repeat steps 2 to 4 for all the grid points.

step6: Reduce the grid spacing and window size by a factor of 2. Repeat the steps from 2 to 5 till the grid spacing becomes one pixel.

The resulting segments are then passed to the Edge refinement stage, which is explained in section 5.B. The merging criterion combines the color composition and spatial texture information. Ideally, a pair of pixels belongs to the same region, if their color composition features are similar and they belong to the same spatial texture category. Thus, to determine if a pair of pixels belongs to the same region, compute the distance between their feature vectors as explained in previous chapters.

B. Edge Refining

Once the crude segmentation is obtained, the edges are refined by adaptively adjusting the borders using the color composition texture features. The approach is similar to that of the ACA. For each pixel in the image, use a small window to estimate the pixel texture characteristics, i.e., a color composition feature vector of the form (2), and a larger window to obtain a localized estimate of the region characteristics. For each texture segment that the larger window overlaps, obtain a separate color composition feature vector, that is, find the average color and percentage for each of the dominant colors. Then, use the OCCD criterion to determine which segment has a feature vector that is closest to the feature vector of the small window, and classify the pixel accordingly. The above procedure could be repeated for each pixel in a raster scan. To save computation, however, consider only the pixels on the border between non-smooth segments or between smooth and non-smooth segments.

A few iterations are necessary for convergence. The iterations converge when the number of pixels that change class is below a given threshold (e.g., equal to the average of the widths of the two windows). Then reduce the window sizes and repeat the procedure. In this work, a series of window pairs starting from 35/5 and ending with 11/3 is used for edge refinement. The window size is odd so that they are symmetric.

6. Results and Analysis

The Proposed algorithm is tested on several types of images and its performance is evaluates and compared with other algorithm by using a standard performance metric.

Segmented outputs for different samples are shown in Fig. 4 (a,e-texture; b-d,f-color-textured). The number of segments for the different samples are summarised in Table 1. Here the crude segmented outputs are taken before the edge refinement stage.

Performance measure

In this work, a relative evaluation method using an area-based approach is used for the evaluation of still image segmentation results as explained in [9].

TABLE 1: RESULTS OF SAMPLE IMAGES

Input Sample Images	Crude segmentation (Number of segments)	Final segmentation (Number of segments)
Sample1	121	14
Sample2	43	9
Sample3	26	9
Sample4	41	19
Sample5	88	45
Sample6	21	6

The evaluation criterion is based on the measure of *spatial accuracy*. Let $S = s_1, s_2, \ldots, s_K$ be the segmentation mask to be evaluated, comprising K regions s_k, $k = 1, \ldots, K$, and let $R = r_1, r_2, \ldots, r_Q$ be the reference mask, comprising Q reference regions r_q, $q = 1, \ldots, Q$. A region is simply defined as a set of pixels p.

For the purpose of evaluating still image segmentation results in accordance with the requirements set in the previous section, a correspondence between the examined segmentation mask and the reference mask has to initially be established, indicating which created region better represents each reference region. This is performed by associating each region r_q of mask R with a different region s_k of mask S on the basis of region overlapping, i.e. s_k is chosen so that $r_q \cap s_k$ is maximized. Let $A = \{(r_q, s_k)\}$ denote the set of region pairs identified using this procedure, and let N_R, N_S denote the sets of non-associated regions of masks R and S, respectively. For every region pair of set A, the criterion of [15] is employed to evaluate the spatial accuracy of the segmentation.

The errors due to inaccurate boundary localization, under-segmentation and over-segmentation calculated for all reference regions. The sum of these error measures, E, for all reference regions and all regions of set N_S, is used for the evaluation of segmentation accuracy. Since it is a measure of error, values of the sum closer to zero indicate better segmentation.

The Performance of this algorithm is evaluated using the above mentioned metrics. The results for the four different images are compared with the reference mask corresponding to that images and found the numerical values, which refers "how much the result is deviated from the reference mask". Hence the result having the value zero is the accurate result

The same input images are given to "Texture Watershed" (TW) [13] and compared the results with the reference mask, which is used for the evaluation of proposed algorithm. The evaluation results for both the algorithms are tabulated in Table 2.

From the performance values of these algorithms, it is easy to conclude that proposed algorithm produces the better and accurate results than texture watershed algorithm.

TABLE 2: EVALUATION RESULTS

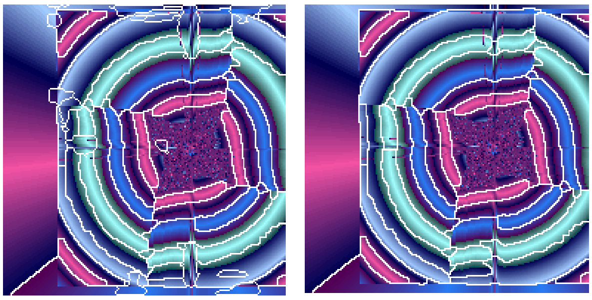
Input Images	Number of seg. in Ref. Mask	Proposed Algorithm		Texture Watershed	
		Number of seg.	Perfor-mance value (error)	Number of seg.	Perfor-mance value (error)
sample1	9	14	297.44	44	1495.60
Sample2	5	9	45.384	15	55.139
Sample3	4	9	6.295	14	7.748
Sample4	7	19	162.592	12	423.43

(a) Sample1

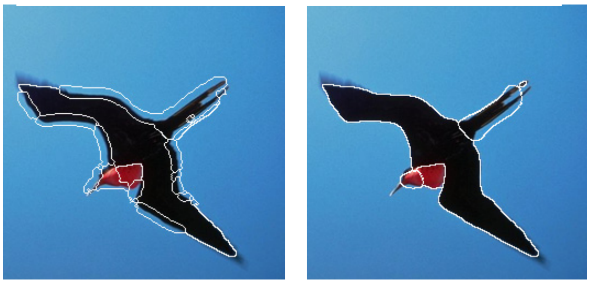
(b) Sample2

(c) Sample3

(d) Sample4



(e) Sample5



(f) Sample6

Figure. 3 Outputs of Color images
Crude segmentation and Final segmentation in column I and II respectively.

7. Conclusion

A new segmentation algorithm is presented for segmenting the natural scenes with two low level features, color and texture. They are independently extracted from the image. Color composition feature is extracted using adaptive clustering algorithm and texture feature is extracted using complex wavelet decomposition. Then, the smooth region of image is segmented using morphological watershed, and non-smooth region is segmented using multigrid region growing. The result is further refined to obtain robust, and at the same time, accurate and precise segmentations. The performance of the proposed algorithms has been demonstrated in the domain of photographic images, including low-resolution images. The performance is also evaluated numerically and compared with other algorithm. From that comparison it is found that the proposed algorithm produces better and accurate results than the existing algorithm. One of the strengths of the algorithm is that it can handle color and texture gradients, which are commonly found in perceptually uniform regions of natural scenes.

Although the method that has been proposed produces a better result than other algorithms, it is computationally inefficient at the color feature extraction. That stage can be replaced by some other techniques to get a same color feature with less computation. The image segmentation results can be used to derive region-specific color and texture features. These can be combined with other segment information, such as location, boundary shape, and size, in order to extract semantic information. Such semantic information may be adequate to classify an image correctly.

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