Perceptually Adapted Color-Texture Image Segmentation Algorithm based on K-dimensional Multi-Step Region Growing

Irene Fondón, Carmen Serrano, Begoña Acha; University of Seville; Seville, Spain

Abstract

This paper presents a new approach for the segmentation of color-textured images, which is based on a novel, perceptually adapted K-means algorithm and a multidimensional multistep region growing technique. The method consists of several steps. Perceptually adapted K-means clustering algorithm is performed to determine the N reference colors of the desired region. Texture features are computed using the energy of some low order statistical moments Then, an N-dimensional multi-step region growing procedure controlled by texture is performed with the automatically extracted seeds by computing, for each new pixel in the image, its perceptual distance to the reference colors, that is, computing the CIEDE 2000 color distance in the $L^*a^*b^*$ *color space to the colors that compound the multicolored texture, rather than Euclidean distance in a non-uniform color space. The method has an adaptive structure due to the growth tolerance parameter that changes with a step size that depends on the mean of the variance for each reference color of the actual grown region. Contrast is also introduced to decide which value of this tolerance parameter is taken, choosing the one that provides the region with the highest mean contrast in relation to the background. Using these tools, a set of 80 natural images is considered. To validate the segmentation results obtained, a comparison with state-of-the-art color-texture based algorithms has been completed. The proposed technique outperformed the published ones achieving a Recall value of 0.757 and a Precision value of 0.812.*

Introduction

Natural scenes are rich in color and texture, and therefore, combining color and texture features would be of significant benefit in distinguishing between regions having the same color but different textures and vice versa [1]. However, texture is in general forgotten in most proposals, probably due to the difficulty in obtaining accurate boundary information when texture, which is a non-local image property, is considered [2]. A review of the literature on image segmentation indicates that a large amount of the past work has focused on developing algorithms based either on color or texture features [1]. The early color-texture segmentation algorithms were design for a particular application and only a few attempts have been made to build a unified segmentation framework [3].

In this paper, a new image region-growing segmentation method, based on color and texture information and related to human perception is proposed. In an ordinary region growing procedure, the belonging condition is fixed, that is, the algorithm grows a region with a determined condition. With the multi-step technique, the belonging condition automatically changes in order to find its optimum value. The multi-step method has been extended to *K* dimensions with *K* the number of reference colors and, moreover, the algorithm is not only based on color but also it is texture-controlled. The major contribution of this work resides in its adapted to human color perception: it uses the quasi-perceptually uniform color space *CIE* $L^*a^*b^*$, the advance color distance metric *CIEDE 2000* and a perceptually adapted *K-means* algorithm.

In the literature there are several color region-growing algorithms. Fan et al. [4] extended Adams and Bischof algorithm [5] to color. They improved the algorithm selecting automatically the seeds and proposed a new method for pixel labeling as well [2]. Cheng [6] published a region-growing approach to color segmentation using 3D clustering and relaxation labeling. The algorithm starts smoothing the image to remove noise. Then the region-growing procedure based on relaxation labeling is performed. As final step it merges regions if they are too small. The three last methods mentioned take only into account color information.

Maeda et al. [7] have proposed a region-growing algorithm that joins color and texture information by applying fuzzy sets, performing a region-growing procedure based on a fixed homogeneity parameter. Yu et al. [8] proposed an improved approach for the *JSEG* algorithm [9] from the aspect of color-texture homogeneity measure. The color discontinuity measure is obtained by a linear combination of given *RGB* sensitivities and its combination with the measure *J* in *JSEG*. The region growing based segmentation, with fixed belonging condition, is performed on the new images *Jc* corresponding to the color measures calculated. García-Ugarriza et al. [10] proposed an automatic color image segmentation algorithm based on dynamic region growing. The initial seeds are computed by analyzing the color gradient dynamic range in order to select a suitable threshold for identifying flat regions. This threshold is also used to define the belonging condition increasing its value in order to add more pixels to the detected seeds. Texture information aids the posterior merging and it is computed by calculating the entropy of image segments on windows of experimentally fixed size. None of the above mentioned color-texture region growing techniques are intended to be perceptually adapted and the color space used is *RGB*.

Though there is an extensive literature on image segmentation, the papers on perceptual segmentation are limited. Among them, Mirmehdi and Petrou [11] proposed a method based on the multiscale perceptual image tower and a probabilistic relaxation method. Shi and Malik [12] proposed a perceptual grouping method based on graph theory, and Manjunath and Ma [13] proposed a technique based on the Gabor filters and the Edge Flow. Recently, Chen et al. [14] proposed the approach based on the adaptive clustering algorithm and the steerable filter decomposition. Maeda et al. [15] proposed a number-driven perceptual segmentation of natural color images using a fuzzy-based hierarchical algorithm. A fuzzy-based homogeneity measure makes a fusion of the *CIE* $L^*a^*b^*$ color by calculating the Euclidean distance and *SGF* texture features on thresholded windows of fixed size. Although these algorithms have a good performance, they are not fully adapted to human perception.

Fully automated operator independent segmentation procedures that successfully segment a general-purpose database are extremely difficult to design. Therefore, usually some kind of operator intervention is required. Manual interaction, typically using a mouse or keyboard, is inevitable [16]. Furthermore, in many contexts (*e.g.* medical imaging), the quality of segmentation can only be judged *a posteriori*, by its pertinence for a particular application. In these cases, an interactive approach is often preferred, where a human operator interprets the semantic contents of the image, selects the objects of interest and the segmentation algorithm is used to extract them automatically from the background [17]. The proposed algorithm has the only requirement of an initial user's participation where he must provide the desired color and texture. To this purpose, the operator draws with the mouse a rectangle within the preferred region. The size of this selection box will be the size of the window for texture calculation making the algorithm perceptually adapted.

In a previously published algorithm, seeds were selected as those pixels whose color difference to the average color of the selection box was low. So it failed with objects with multicolored textures, or shades, [18]. In [19] colors existing in the texture to be segmented were found and those pixels whose color difference to any of these colors were considered as seeds. In the proposed approach colors existing in a particular texture are determined with a clustering technique adapted to human perception [20].

Color and Texture Features

Color information

To perform color segmentation a uniform color space is required. That is, in the chosen color space, distance measures must be correlated with perceived color differences. In 1976, *CIE* proposed two color spaces that approximately possessed this property: $L^*a^*b^*$ and $L^*u^*v^*$. Euclidean distances in those spaces were believed to be approximately correlated with perceptual color differences. Later on it was demonstrated that this goal was not strictly achieved. To improve the uniformity of color difference measurements in *CIE* $L^*a^*b^*$, an empirical modification of the Euclidean distance was proposed in 1995. This distance measure is abbreviate called *CIE94*. More recently, the *CIE* has established the *CIEDE 2000* color difference equation that extends the concept of *CIE94* with further complexity. It has been demonstrated that *CIEDE 2000* performs better than all the existing color distance formulas including the new Euclidean distance in the log compressed OSA-UCS space [21], [22].

Texture information

Texture information plays a significant role in image interpretation. Human beings are able to distinguish in an image those regions that are equal in color but different in texture. Our goal is to take advantage of this additional information treating it not as a problem but as a useful tool.

The proposed method extracts texture features only from the luminance component (L^*) of the original image and not from the chrominance ones (a^*, b^*). This assumption is based on previous works: the psychophysical studies of Poirson and Wandell suggest that color and pattern information in the human visual system are processed separately [23]. Mojsilovic et al. [24], suggest that the overall perception of color patterns is formed through the interaction of a luminance component, a chrominance component and an achromatic pattern component. The luminance and chrominance components are used in extracting color-based information, while the achromatic pattern component is utilized as texture pattern information. So, they state that human perception of pattern is unrelated to the color content of an image. Mäenpää and Pietikäinen [25] conclude that it seems that texture information should be extracted from the luminance component, whereas color is more a regional property.

The texture features employed in this method are based on some local low statistical moments [26]. In order to justify the choice of first order statistics for texture feature extraction, Zamperoni et al. [27] state that although one can construct some patterns for which the choice of first order statistics does not work, the converse is true for a surprisingly high number of real images representing natural scenes of a given type, as confirmed by the experiments reported in Lowitz [28] and in Kim [29].

Furthermore, as this algorithm is applied to general-purpose images, the texture present in this kind of images represents properties such as smoothness, coarseness, regularity, etc. rather than the arrangement of image primitives, Figure 6. In textures where a primitive is repeated, structural methods, spectral methods or techniques based on second-order statistics, such as the coocurrence matrix could work better [27]. But this does not happen in images where patterns are not present.

The algorithm calculates for every pixel, four statistical moments m_{pq} with p,q={0,1} by processing the L^* component with local masks expressed in a normalized coordinate system. A formal expression of these moments is shown in equation (1).

$$
\begin{aligned}
&m_{pq} = \frac{1}{W^2} \sum_{m=i-W/2}^{i+W/2} \sum_{n=-j-W/2}^{j+W/2} f(m,n) x_m^p y_n^q; \\
&x_m = \frac{m-i}{W/2};\; y_n = \frac{n-j}{W/2}; \\
&i,j \in image,\, p,q = 0,1
\end{aligned} \tag{1}
$$

where W is the window width, (i,j) are the pixel coordinates for which the moments are computed, (m,n) the coordinates of another pixel which falls within the window, $(x_m\ y_n)$ are the normalized coordinates for (m,n), and $f(m,n)$ is the value of the L^* component at the pixel with coordinates (m,n). This normalized expression leads us to compare among pixel moments and it is equivalent to the finite convolution of the image with a mask. The sizes of these masks have been fixed to the size of the selection box. Usually, for each segmentation this size will be different, so our algorithm will be automatically adapted to the texture we want to isolate.

With all these parameters, we can build four new images M_{pq} with p,q={0,1} corresponding to each statistical parameter. To this purpose we assign to each pixel a value equal to the previously calculated moment m_{pq}. For example, in the case of pixel (30, 20) if we want to build the image M_{11} we define the value at position (30, 20) as the moment m_{11}, calculated with a window centered in that pixel.

We must notice that we have included the moment m_{00}, because it is an important feature to characterize the texture. The mean of the luminance in a texture is very significant.

The presence of shaded areas in an object will make this moment to vary but this is not a problem in terms of perception:

as we are separating different appearances, when the same object is partly in shade, it is perceived as two different regions.

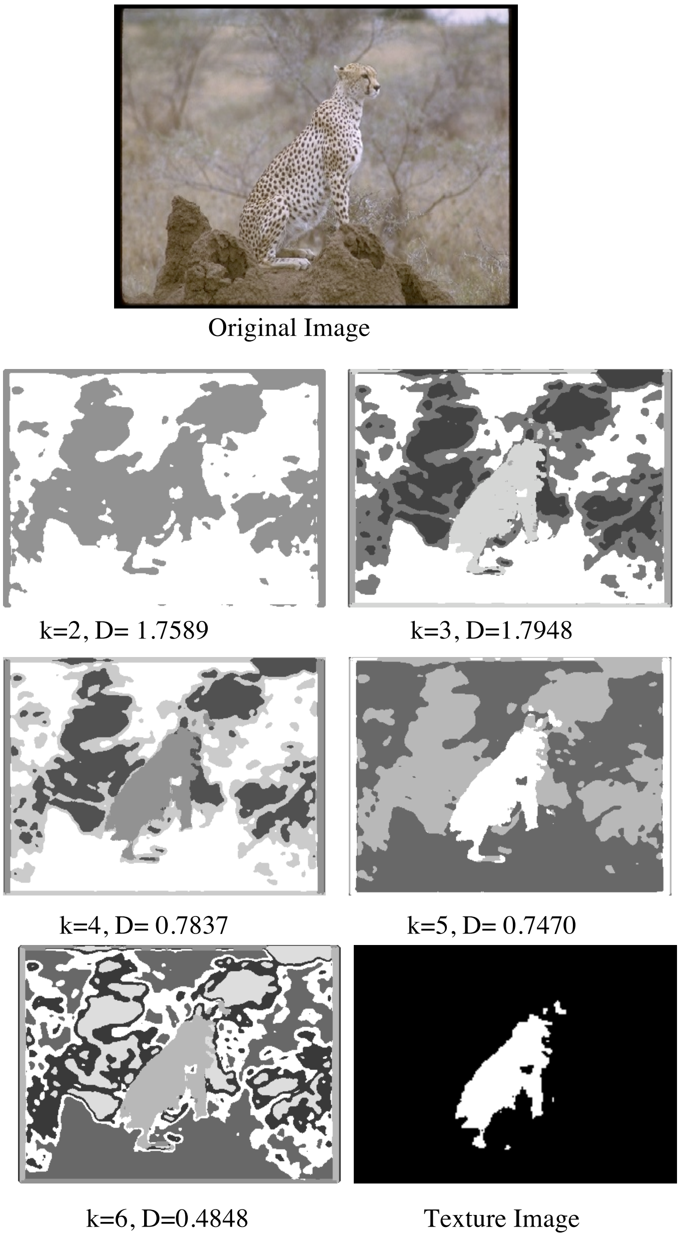

***Figure 1**. Texture of the original image is analyzed in order to isolate the leopard. After the perceptually adapted statistical moment evaluation, and energy computing, the results of the k-means algorithm are shown for different t values of k. The corresponding values for Dunn's coefficient are also shown, giving its maximum for k=3, which leads to the texture image displayed.*

Afterwards, we defined new images calculated from the energy of the moments. We called them *energy images E00*, *E01*, *E10* and *E11* and they represent the strength of each moment around the pixel location. The computation of the energies follows equation (2).

$$E_{pq}(i,j) = \frac{1}{W^2} \sum_{m=i-W/2}^{i+W/2} \sum_{n=j-W/2}^{j+W/2} M_{pq}{}^2(m,n) \quad (2)$$

where $E_{pq}(i,j)$ is the energy corresponding to the pixel with coordinates (i,j) in the image M_{pq}, W is the window width, $M_{pq}(m,n)$ is the value of the pixel with coordinates (m,n) in the moment image M_{pq} and $p,q=\{0,1\}$

Therefore the texture of each pixel is now characterized with four values, one from each energy image. Then a pixel can be interpreted as a point in a four dimensional space. Subsequently, in order to assign each pixel to one texture in the image, we apply the traditional k-means algorithm in this space. The number of textures presents in the image is determined with Dunn's coefficient [30].

At the end of this procedure the image is divided into a number of textures. This information will control the region growing. In Figure 1 the performance of this procedure is illustrated.

Texture-controlled K-dimensional Multistep Region Growing

The general scheme of the algorithm is shown in Figure 2.

Preprocessing

Original images may include some noise that could change the result of the segmentation. A filtering or non-linear smoothing approach using anisotropic diffusion is applied on the original image to smooth unwanted data. This method is stronger in the homogeneous parts of the image and weaker in the edges [31]. In other words, it has the property of eliminating noise while preserving edges, which is a desirable characteristic in color segmentation. Moreover, as we are processing color images, the most effective method to perform the diffusion is to apply it to the intensity and chromaticity separately [32].

Reference colors determination

After the preprocessing, colors present in the selection box have to be determined. In the proposed approach colors existing in a particular texture are determined with a clustering technique adapted to human perception [33]. This clustering can be summarized as follows.

Let $X=\{x_1,\ldots, x_n\}$ be the pixels contained in the selection box represented in the $L^*a^*b^*$ color space. The codebook V is defined as the set $V = \{v_1,\ldots, v_k\}$, whose elements are the centroids or reference colors. The Voronoi set π_i of the codevector v_i is the subset of X for which the centroid v_i is the nearest vector: Starting from the finite data set X, this algorithm moves iteratively the k codevectors to the centroids of their Voronoi sets and recalculates the Voronoi sets. The codebook V is chosen to minimize the empirical quantization error:

$$E(V) = \frac{1}{2n} \sum_{i=1}^{K} \sum_{x \in \pi_i} d^2(x, v_i) \quad (3)$$

where d is the distance measure and n the number of pixels. In the case of the Euclidean distance, this error is minimized when the codevectors are chosen as:

$$v_i = \frac{1}{|\pi_i|} \sum_{x \in \pi_i} x \quad (4)$$

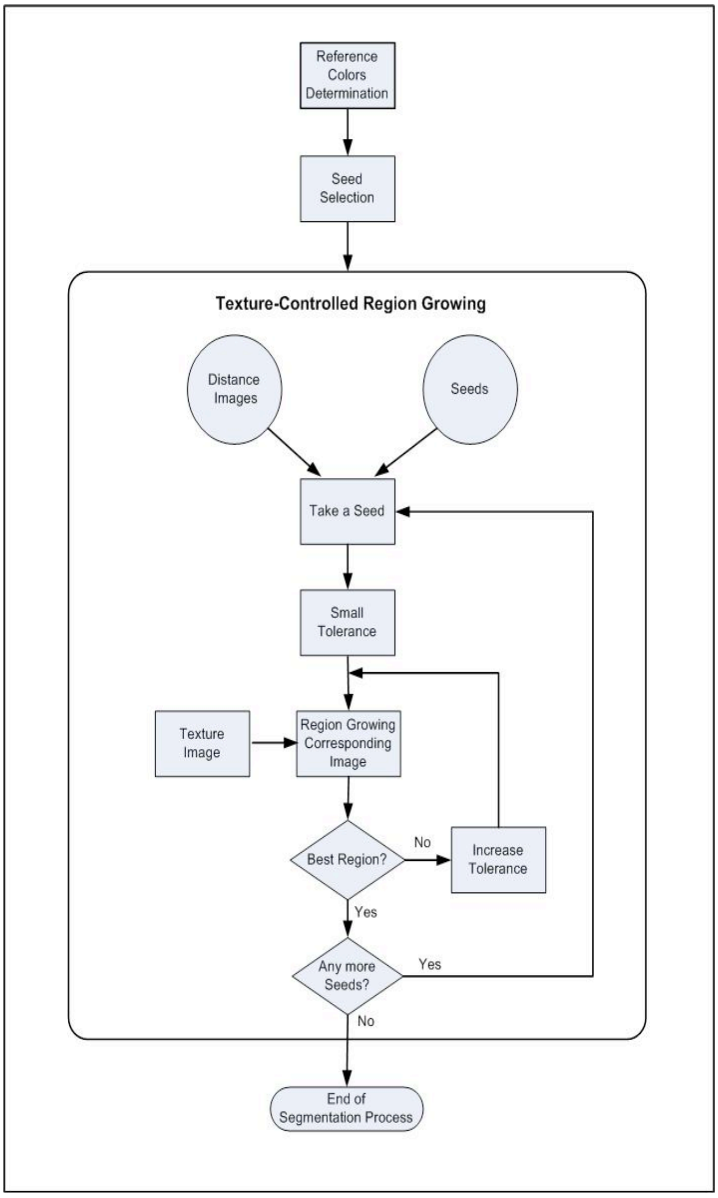

Figure 2. *General scheme of the Texture-Controlled K-dimensional Multistep Region Growing algorithm.*

The *CIEDE 2000* color distance between two pixels of color values and is calculated as:

$$\Delta E_{00}^{*} = \left[\left(\frac{\Delta L'}{k_L S_L}\right)^2 + \left(\frac{\Delta C'_{ab}}{k_C S_C}\right)^2 + \left(\frac{\Delta H'_{ab}}{k_H S_H}\right)^2 + R_T\left(\frac{\Delta C'_{ab}}{k_C S_C}\right)\left(\frac{\Delta H'_{ab}}{k_H S_H}\right)\right]^{1/2} \quad (5)$$

where the values of the parametric factors and the weighting functions can be found in [21]. As it was already mentioned, the codebook V is chosen to minimize the error (3).To solve this optimization problem, the clustering technique described in [33] employs the *2-D*-log-search [34]-[35], extended to *3-D*.

It has a recursive structure and looks among some selected points of the neighborhood for the one that minimize the objective function, that is, the one that minimize the sum of the quadratic distances of each point to each centroid in each cluster.

To obtain the value K (number of clusters) automatically, we use, once more, Dunn's coefficient [30].

On Figure 3 we can see an example showing the corresponding reference colors for the original image of Figure 1.

Figure 3*. Perceptually detected colors, (a) and (b), on the multicolor texture of the original image of Figure 1.These are the reference colors.*

Seed selection

A particular pixel will be selected as seed if it fulfills the following three conditions:

1) Its CIEDE2000 color difference to any reference colors is a local minimum. That is, all its neighbors have a color difference to any reference color higher than that pixel.

2) Its CIEDE2000 color difference to any of the reference colors has to be lower than a threshold.

This threshold is calculated automatically as follows. A histogram with the distances to each of the reference colors is calculated, Then, K thresholds are calculated as the peaks in the lowest mode of the histograms. Obviously, the only thing what matters for the good performance of the algorithm is that seeds must belong to the region to be segmented and, provided this condition is met, the choice of a particular threshold for the seeds is not decisive in the success of the segmentation. The procedure to find significant peaks and valleys and the threshold follows the algorithm developed by Acha et al. [36]

3) Finally, texture information is applied to reject some of the seed candidates: seeds must have been classified as the same texture than one of the selection box. An example summarizing the seed selection procedure for the image in Figure 1 is shown in Figure. 4.

Region Growing

We use a *K*-dimensional perceptually adapted dynamic region growing method to segment the image.

The original idea introduced by this method is that, in an ordinary region growing, the merging condition is fixed. For each seed, the algorithm grows a region with a particular inclusion condition. With this multi-step technique, the merging condition automatically changes in order to find its optimum value, which will correspond to the highest value of the contrast parameter explained later on in this subsection.

After the seed selection process, we have K-groups of seeds, one group for each of the reference colors. Let us take a particular seed belonging to the group i. The process begins with a typical region growing procedure where a pixel to join the growing region must fulfill three conditions:

1) It cannot belong to another region grown before.

2) It must have the same texture as the seed.

3) The perceptual distance to any reference color n, must be lower than a threshold. This similarity is measured according to (6):

$$\frac{F_{\max,n} + F_{\min,n}}{2} - \tau \le F_{ij,n} \le \frac{F_{\max,n} + F_{\min,n}}{2} + \tau \quad n = 1,\ldots,K \tag{6}$$

where n refers to the reference color n, K is the number of reference colors, $F_{max,n}$ and $F_{min,n}$ are the maximum and minimum values of the perceptual distances of the pixels in the growing region for color n, i and j are the coordinates of the pixel, $F_{ij,n}$ is the perceptual distance of the actual pixel to the reference color n, and τ is the tolerance step, which will be iteratively increased.

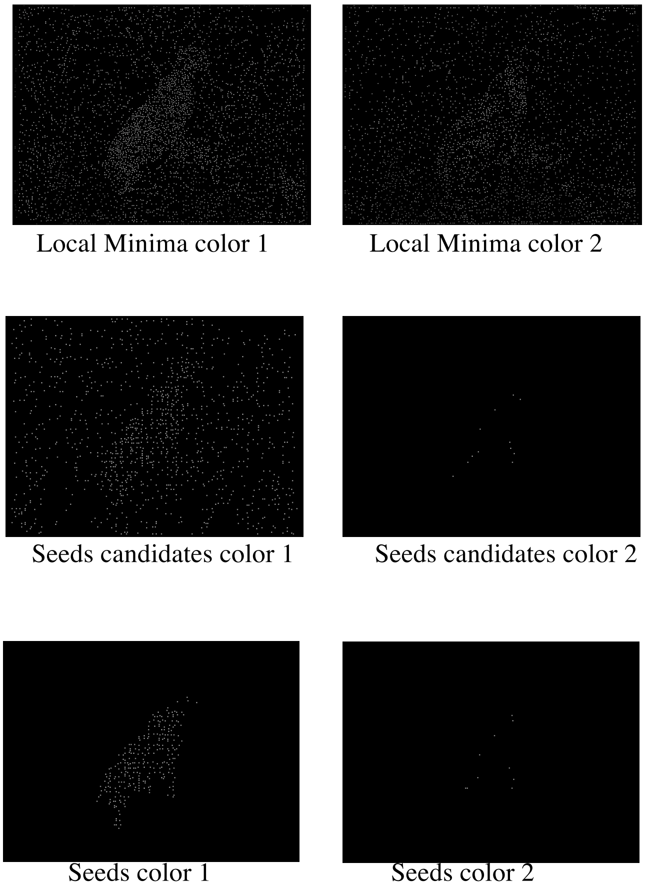

***Figure 4**. Seed selection process. Firstly pixels with lowest perceptual distance to the reference colors are obtained. These minima are subsequently thresholded to obtain seeds candidates. When texture information is included, final seeds are attained.*

It must be emphasized that the region growing does not depend on the position of the seed within the region. Although a boundary is encountered on one side, the algorithm will continue growing with the same parameter of tolerance in the other directions until no other pixel can be included in the region; and only then, contrast is calculated to determine if we should increase the tolerance and continue growing.

Once a region is grown with a particular τ, the next step is to verify whether the region obtained is optimal. If it is not optimal, the region growing will continue growing with a more relaxed condition, that is, τ is increased. More specifically, τ follows the expression:

$$\tau = \alpha \cdot \sigma \tag{7}$$

where σ is the standard deviation of the perceptual distances of the pixels added before to the region and α is variable with an initial value experimentally fixed to 0.1. On each iteration α is increased by 0.1. Then, the region growing is repeated with this more relaxed condition.

The optimality criterion to choose the best region during the region-growing process or stop condition consists in maximizing a contrast parameter. This contrast parameter is calculated for each reference color as:

$$contrast = \frac{\left|\overline{Inside\ edge} - \overline{Outside\ edge}\right|}{\overline{Inside\ edge} + \overline{Outside\ edge}} \tag{8}$$

where *Inside edge* and *Outside edge* represent the mean perceptual distance values of the pixels belonging to the inner border and outer border of a region respectively.

At the beginning, the region growing has a very restrictive merging condition. This will lead us to obtain a small region. Repeating the process, the contrast parameter of equation (8) is calculated.

While the grown region is inside the object, the contrast parameter increases its value in a smooth way, because pixels belonging to the inner border and to the outer border of the region are similar. When the region whose contrast is being calculated matches the object, the contrast parameter has a high value because pixels surrounding the region will differ from those inside the region. If we continue growing, the contrast parameter will be low again because both the inner border and the outer border are similar. Therefore when the contrast parameter reaches its maximum we have obtained the best region.

A steep slope in the contrast parameter evolution corresponds to those values of α for which boundaries are reached. This increase may be either because the whole boundary of the object has been reached or because the boundary of the region grown matches in part the boundary of the object. In the second situation, the tolerance will continue being increased until the whole boundary is reached.

During this increase of the parameter α, the contrast parameter never decreases and, as a consequence, the stop condition is not reached, because the increase of the tolerance is not high enough to overcome a boundary.

Once the whole boundary is reached, if the tolerance is being enlarged again the region will exceed the limits of the object and, therefore, the contrast will decrease. In such a situation the region growing will stop because the stop condition has been attained.

This process is iteratively repeated for every seed belonging to each group ($n=1,\ldots,K$) corresponding to the reference colors. If a seed has been already included in the region it is omitted.

On Figure 5, the result obtained for the leopard image taken as an example in the document is shown. The skin of the leopard having the desired color and texture is marked in pink.

Experimental results

In our experiments, we tested the performance of the proposed segmentation method using 80 real-world images containing texture regions taken from the commercial Corel stock photo collection.

Figure 5. *Final segmentation of the original image is shown in Figures 1 and 2. Pixels in pink are considered to belong to the desired region.*

The validation test has been performed by comparing the results of the algorithm with two state-of-the-art algorithms, *CTREG* [18] and Carson's work [37], and with the manual segmentation carried out by five observers. *CTREG* algorithm has an analogous structure but it does not take into account all the possible reference colors. Instead, it is based on the mean color of the selected region and it does not have a perceptually adapted *K*-means procedure. Carson's work is an algorithm that segments natural images based on texture and color information and its results are available in the Internet (http://elib.cs.berkeley.edu/photos/blobworld).

In order to analyze the performance of the algorithm in an objective way, two parameters have been calculated. The first parameter is the *Precision* or *Positive Predictive Value* (PPV), which measures the ratio between the number of pixels segmented by the algorithm which fit the segmentation gold standard and the total amount of pixels segmented. The second parameter is called *Recall* or *Sensitivity* (S) and it is the ratio between the number of pixels segmented by the algorithm which fit the segmentation gold standard and the total amount of pixels in the segmentation gold standard. To estimate this "ground truth" segmentation from the group of five experts, we have used the method based on Expectation-Maximization (EM) proposed in [38]. The expert segmentation decision at each pixel is directly observable and the hidden ground truth is a binary variable for each pixel. The complete data consists of the expert decisions, which are known, and the ground truth, which is not known. If the ground truth were known it would be straightforward to estimate the expert quality parameters. Since the complete data is not available, the ground truth is replaced with their expected values under the assumption of the previous estimate of the expert quality parameters. Then, the expert quality parameters are re-estimated iterating this sequence of estimation of the quality parameters and ground truth variables until convergence is reached.

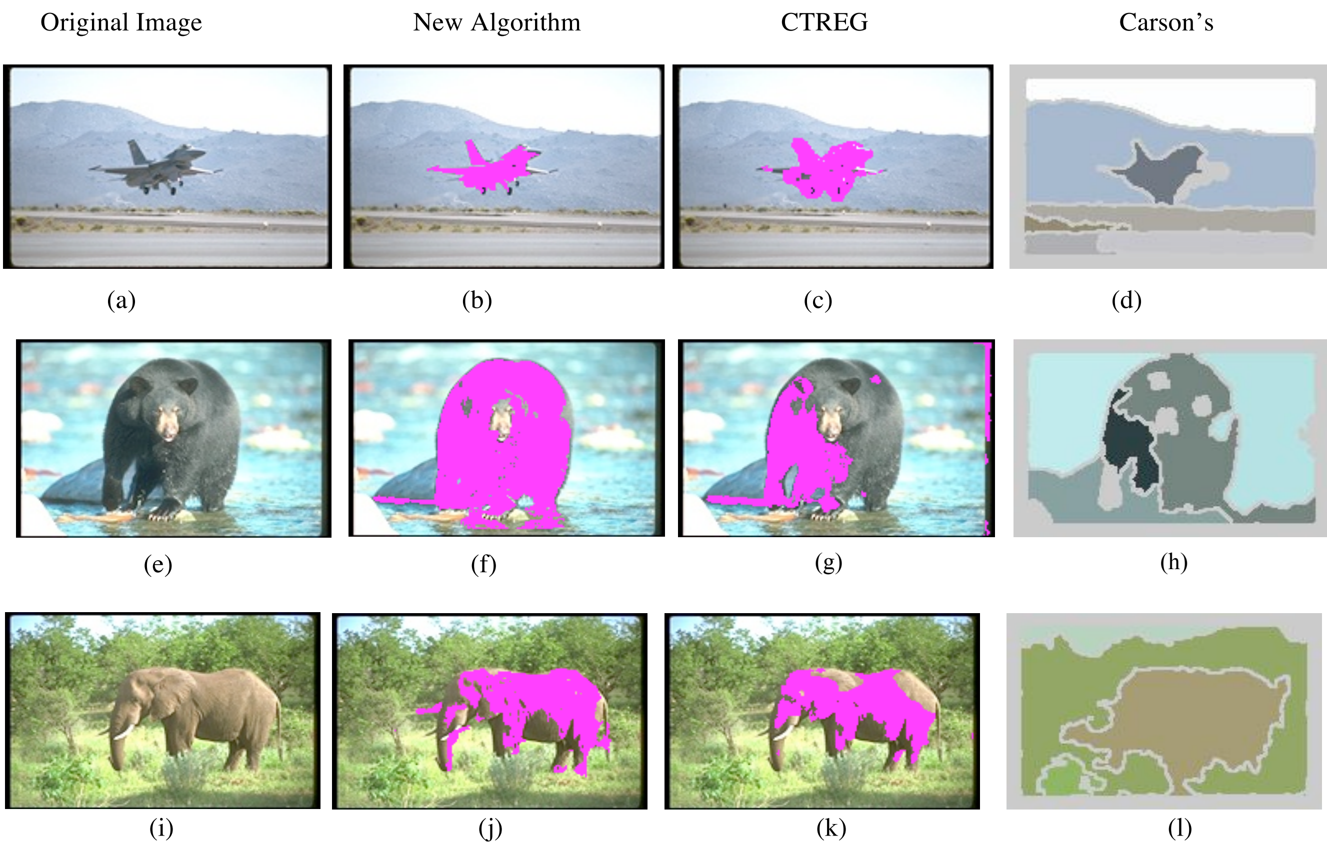

Figure 6*. Three results are shown: (a), (e) and (i) are the original images, (b), (f) and (j) are the results obtained with the proposed algorithm, (c), (g) and (k) are the images segmented by CETREG. (d), (h) and (l) are Carson's results.*

Intuitively it can be seen that the first parameter measures the over-segmentation, which would be null if *Precision* were 1. Likewise, *Recall* measures the under-segmentation. The segmentation Gold Standard was obtained from observer's segmentation by applying an Expectation Maximization validation algorithm [38]. Regarding to the 80 Corel images, the experimental data is depicted in Table I and shows over all *Recall* and *Precision* values as well as its standard deviations. The algorithm achieves a *Recall* of 0.757 for a *Precision* of 0.812 while *CTREG* achieves a *Recall* of 0.695 and a *Precision* of 0.807. Carson's algorithm achieves a *Recall* of 0.685 and a *Precision* of 0.629. We can observe that although in terms of *Precision* three methods are very similar, the new version provides a significant improvement in *Recall* while *Precision* is also improved. Then, regarding to *Precision* our algorithm outperforms Carson's one and has a similar value to the previously published approach. In Fig. 6 some images segmented with the three algorithms are presented. Fig. 6 *(b), (f)* and *(j)* show segmentation results of the proposed algorithm, *(c), (g)* and *(k)* are the images segmented by *CETREG*. *(d), (h)* and *(l)* are Carson's results. Carson's method segments the whole image into regions with the same color and texture, and in the resulting image each region is shown in a different color. In the proposed algorithm only the region with the same texture and color than the selection box is colored in pink. The same occurs with *CETREG*. It should be noted that in Fig. 6 (*c*) and (d) do not obtain an accurate region boundary. As for the segmentation of the bear, (f) and (g) show an over-segmented final region. As the proposed algorithm includes all colors present in the bear (gray, black and its shaded versions) the result is more suitable. Talking about the last example, (l) gives the worst result for this difficult image. The proposed algorithm, includes in the final region more pixels than *CETREG* algorithm getting closer to the desired result.

Table I: *Recall* and *Precision* values for the three methods.

	Proposed algorithm	*CTREG*	Carson's algorithm
S mean	0.757	0.695	0.685
S standard deviation	0.161	0.191	0.213
PPV mean	0.812	0.807	0.629
PPV standard deviation	0.163	0.208	0.307

Conclusions

In this paper, a new method for natural color image segmentation has been proposed. The approach is perceptually adapted because image is represented in *CIE* $L^*a^*b^*$ color space and *CIEDE 2000* color distance. Thus, the algorithm identifies the *K* colors of the desired region trough the clustering technique *K*-means adapted to human perception. Once these colors are identified, the segmentation procedure based on a *K*-dimensional texture controlled multi-step region growing technique is performed. Contrast is introduced to decide whether a region is the best or not. Hence, both color and texture information are used in order to fulfill the requirements of real color images. The method has been validated with 80 natural images and the results have been compared to manual segmentations and to the results provided by two published algorithms, yielding better values in terms of *Recall* and *Precision*.

References

[1] M. S. Allili and D. Ziou, Globally adaptive region information for color-texture image segmentation, Pattern Recognition Letters, 28, pg. 1946-1956 (2007).

[2] J. Fan, G. Zeng, M. Body and M. Hacid, Seeded region growing: an extensive and comparative study. Pattern Recognition Letters, 26, pg. 1139-1156 (2005).

[3] D. E. Ilea and P. F. Whelan, Ctex- An Adaptive Unsupervised Segmentation Algorithm Based on Color-Texture Coherence, IEEE Transaction on Image Processing, Vol. 17, Nº 10, pg. 1926-1937, (2008).

[4] J. Fan, D. K. Yau, A. K. Elmagarmid, W. G. Aref, Automatic image segmentation by integrating color-edge extraction and seeded region growing. In IEEE Trans. on Image Processing, Vol. 10, Nº 10, pg. 1454-1466, (2001).

[5] R. Adams, and L. Bischof, Seeded region growing, IEEE Trans. on Pattern Analysis and Machine Intelligence, Vol. 16, Nº 6, pg. 641-647, (1994).

[6] S. C. Cheng, Region-growing approach to colour segmentation using 3-D clustering and relaxation labeling. IEEE Proc. Vis. Image Signal Process, Vol. 150, Nº 4, pg. 270-276, (2003).

[7] J. Maeda, S. Novianto, S. Saga, Y. Suzuki, V. Anh, 1999. Rough and accurate segmentation of natural images using fuzzy region-growing algorithm. Proc. Int. Conf. on Image Processing, 3, pg. 227-231, (1999).

[8] S. Yu, Y. Zhang, Y. Wang and J. Yang, Unsupervised Color-texture Image Segmentation, Journal of Shanghai Jiaotong University (Science), Vol. 13, Nº 1, pg. 71-75, (2008).

[9] Y. Deng and B. S. Manjunath, Unsupervised Segmentation of color-texture regions in images and video. IEEE Trans. On PAMI, Vol. 23, Nº 12, pg. 1338-1350, (2001).

[10] L. García-Ugarriza, E. Saber, V. Amuso, M. Shaw and R. Bhaskar, Automatic Color Image segmentation by Dynamic Region Growth and Multimodal Merging of Color and Texture Information, IEEE Int. Conf. on Acoustic, Speech and Signal Processing, pg. 961-964, (2008).

[11] M. Mirmehdi and M. Petrou. Segmentation of color textures. *IEEE* Transactions on Pattern Analysis and Machine Intelligence, Vol. 2, Nº 2, pg. 142-159, 2000.

[12] J. Shi and J. Malik, Normalized Cuts and Image Segmentation, IEEE Transaction on Pattern Analysis and Machine Intelligence, Vol. 22, Nº 8, pg. 888-905, (2000).

[13] W. Y. Ma and B. S. Manjunath, EdgeFlow: a technique for boundary detection and image segmentation. IEEE Transactions on Image Processing, Vol. 9, Nº8, pg. 1375-1388, (2000).

[14] J. Chen, T. N. Pappas, A. Mojsilovic and B. E. Rogowitz, Image Segmentation by Spatially Adaptive Color and Texture Features, IEEE International Conference on Image Pocessing, Vol. 1, pg. 1005–1008, (2003).

[15] J. Maeda, A. Kawano, S. Saga, and Y. Suzuki, Number-Driven Perceptual Segmentation of Natural Color Images for Easy Decision of Optimal Result, IEEE International Conference on Image Pocessing, Vol. 2, pg. 265-268, (2007).

[16] M. Sadeghi, G. Tien, G. Hamarneh, and M. S. Atkins, Hands-free Interactive Image Segmentation Using Eyegaze, Medical Imaging 2009: Computer-Aided Diagnosis, Proc. of SPIE, Vol. 7260, pg. 72601H-1-72601H-10 (2009).

[17] P. Arbeláez and L. Cohen, Constrained Image Segmentation from Hierarchical Boundaries, IEEE Computer Society Conference on Computer Vision and Pattern Recognition CVPR 2008, (2008).

[18] I. Fondón, C. Serrano and B. Acha, Color-Texture Image Segmentation based on Multi-Step Region Growing, Optical Engineering, The International Society for Optical Engineering (SPIE), Vol. 45, Nº5, pg. Pag. 057002-1-057002-9, (2006).

[19] I. Fondón, C. Serrano, B. Acha, Color and Texture Based Segmentation Algorithm for Multicolor Textured Images, Visapp 2007. Proceedings of the Second International Conference on Computer Vision Theory and Applications. International

Conference on Computer Vision Theory and Applications, pg. 258-263, (2007).
[20] B. Acha, C. Serrano, I. Fondón, Perceptual Color Clustering for image segmentation based on CIEDE 2000 color distance, 11th Congress of the International Colour Association, AIC 2009, (2009).
[21] M. R. Luo and G. Cui, B. Rigg, The development of the CIE 2000 colour-difference formula: CIEDE2000, Color Research & Application, Volume 26 Issue 5, Special Issue: Special Issue on Color Difference, pg. 340–350, (2001).
[22] G. Cuo and M. R. Luo, Testing Colour-Difference Formulae And Uniform Colour Spaces Using Small Colour Difference Datasets, 11th Congress of the International Colour Association, AIC 2009, (2009).
[23] B. Poirson and B. Wandell, Pattern-color separable pathways predict sensitivity to simple colored patterns. Vision Res., Vol. 36, Nº4, pg. 515-526, (1996).
[24] A. Mojsilovic, J. Kovacevic, D. Kall, R. Safranek and S. Ganapathy,. Matching and retrieval based on the vocabulary and grammar of color patterns, IEEE Transactions on Image Processing, Vol. 9, Nº1, pg. 38-54, (2000).
[25] T. Mäenpää and M. Pietikäinen, Classification with color and texture: jointly or separately?, Pattern Recognition, Vol. 37, pg. 1629-1640, (2004).
[26] M. Tuceryan, Moment based texture segmentation, Pattern Recognition Letters, Vol. 15, Nº7, pg. 659-668, (1994).
[27] P. Zamperoni, Model-free texture segmentation based on distances between first-order statistics. Digital Signal Processing, Vol. 5, pg. 197-225, (1995).
[28] G. Lowitz, Can a local histogram really map texture information?, Pattern Recognition, Vol. 2, pg.141-147, (1983).
[29] V. Kim and Y. P. Yaroslavskii, Rank algorithms for picture processing, Comput. Vision Graphics Image Process, Vol. 35, pg. 234-258, (1986).
[30] U. Maulik, S. Bandyopadhyay, Performance evaluation of some clustering algorithms and validity indices. IEEE Transaction on Pattern Analysis and Machine Intelligence, Vol. 24, Nº 12, pg. 1650-1654, (2002).
[31] P. Perona and J. Malik, Scale-space and edge detection using anisotropic diffusion. In IEEE Trans. on Pattern Analysis and Machine Intelligence, Vol.7, pg. 629-639, (1990).
[32] L. Lucchese and S. K. Mitra, Color segmentation based on separate anisotropic diffusion of chromatic and achromatic channels, IEEE Proceedings: Vision, Image, and Signal Processing, Vol. 3, pg. 141-150, (2001).
[33] B. Acha, C. Serrano, I. Fondón, Perceptual Color Clustering for image segmentation based on CIEDE 2000 color distance, 11th Congress of the International Colour Association, AIC 2009, (2009).
[34] Mordecai Avriel, Nonlinear Programming: Analysis and Methods (*Dover Publishing*, 2003) pg. 288.
[35] Jan A. Snyman, Practical Mathematical Optimization: An Introduction to Basic Optimization Theory and Classical and New Gradient-Based Algorithms, (Springer Publishing, 2005) pg.97.
[36] B. Acha, C. Serrano, J. I. Acha, L. M. Roa, CAD tool for burn diagnosis, Lecture Notes in Computer Science (Springer), Vol. 2732, pg. 294-305, (2003).
[37] C. Carson, S. Belongie, H. Greenspan and J. Malik, Blobworld: image segmentation using expectation-maximization and its application to image querying, Third Int. Conf. on Visual Information and Information Systems, LNCS, Vol. 1614, pg. 509-516, (1999).
[38] S. K. Warfield, K. H. Zou and W. M. Wells, Validation of image segmentation and expert quality with an expectation-maximization algorithm, MICCAI 2002 Fifth Int. Conf. on Medical Image Computing and Computer Assisted Intervention, pg. 298-306, (2002).

Author Biography

Irene Fondón received the M.S. degree in Telecommunication Engineering from the University of Seville, Spain, in 2004. She has been working as an associated professor since 2005 in the Signal Processing and Communications Department of the University of Seville. She is currently working toward her PhD degree. Her current research activities include works in the field of image processing and its medical applications. She is author of papers both in journals and international conferences.

Carmen Serrano received the M.S. degree in Telecommunication Engineering from the University of Seville, Spain, in 1996 and the Ph.D. degree in January 2002. In 1996, she joined the Signal Processing and Communication Department at the same university, where she is currently an associated Professor. Her research interests concern image processing and, in particular, color image segmentation, classification and compression, mainly with biomedical applications. She is author of numerous papers both in journals and international conferences.

Begoña Acha received the Ph.D. degree in Telecommunication Engineering in July 2002. In 1996, she joined the Signal Processing and Communication Department at the same university, where she is currently an associated Professor. Her current research activities include works in the field of color image processing and its medical applications, in particular in segmentation, classification and compression. She is author of numerous papers both in journals and international conferences.