Colour Texture Segmentation by Region-Boundary Cooperation

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Abstract. A colour texture segmentation method which unifies region and boundary information is presented in this paper. The fusion of several approaches which integrate both information sources allows us to exploit the benefits of each one. We propose a segmentation method which uses a coarse detection of the perceptual (colour and texture) edges of the image to adequately place and initialise a set of active regions. Colour texture of regions is modelled by the conjunction of non-parametric techniques of kernel density estimation, which allow to estimate the colour behaviour, and classical co-occurrence matrix based texture features. When the region information is defined, accurate boundary information can be extracted. Afterwards, regions concurrently compete for the image pixels in order to segment the whole image taking both information sources into account. In contrast with other approaches, our method achieves relevant results on images with regions with the same texture and different colour (as well as with regions with the same colour and different texture), demonstrating the performance of our proposal. Furthermore, the method has been quantitatively evaluated and compared on a set of mosaic images, and results on real images are shown and analysed.

1 Introduction

Image segmentation has been, and still is, a relevant research area in Computer Vision, and hundreds of segmentation algorithms have been proposed in the last 30 years. Many segmentation methods are based on two basic properties of the pixels in relation to their local neighbourhood: discontinuity and similarity. Methods based on pixel discontinuity are called boundary-based methods, whereas methods based on pixel similarity are called region-based methods. However, it is well known that such segmentation techniques - based on boundary or region information alone - often fail to produce accurate segmentation results [1]. Hence, in the last few years, there has been a tendency towards algorithms which take advantage of the complementary nature of such information.

Reviewing the different works on region-based segmentation which have been proposed (see surveys on image segmentation [2,3]), it is interesting to note the evolution of region-based segmentation methods, which were initially focused on

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grey-level images, and which gradually incorporated colour, and more recently, texture. In fact, colour and texture are fundamental features in defining visual perception and experiments have demonstrated that the inclusion of colour can increase the texture segmentation/classification results without significantly complicating the feature extraction algorithms [4]. Nevertheless, most of the literature deals with segmentation based on either colour or texture, and there is a limited number of systems which consider both properties together.

In this work we propose a new strategy for the segmentation of colour texture images. Having reviewed and analysed more than 50 region-boundary cooperative algorithms, we have clearly identified 7 different strategies (see [5]) to perform the integration. As a natural development of this review work, we defined a new strategy for image segmentation [6] based on a combination of different methods used to integrate region and boundary information. Moreover, to knowledge of the authors, there has not yet been any proposal which integrates region and boundary information sources while taking colour and texture properties into account. Hence, we have extended our previous approach to deal with the problem of colour texture segmentation. We focus on "color texture" taking into account that is both spatial and statistical. It is spatial since texture is the relationship of groups of pixels. Nothing can be learned about texture from an isolated pixel, and little from a histogram of pixel values.

The remainder of this paper is organised as follows: a review of the recent work on color texture segmentation concludes this introduction. Section 2 describes the proposed segmentation strategy detailing the placement of starting seeds, the definition of region and boundary information and the growing of active regions. The experimental results concerning a set of synthetic and real images demonstrating the validity of our proposal appear in Section 3. Finally, conclusions are given in Section 4.

1.1 Related Work

Most of the literature deals with segmentation based on either colour or texture. Although colour is an intrinsic attribute of an image and provides more information than a single intensity value, there has been few attempts to incorporate chrominance information into textural features [4]. This extension to colour texture segmentation was originated by the intuition that using information provided by both features, one should be able to obtain more robust and meaningful results.

A rather limited number of systems use combined information of colour and texture, and even when they do so, both aspects are mostly dealt with using separate methods [7]. Generally, two segmentations are computed for colour and texture features independently, and obtained segmentations are then merged into a single colour texture segmentation result with the aim of preserving the strength of each modality: smooth regions and accurate boundaries using texture and colour segmentation, respectively [8,9]. The main drawback is related to the selection rule for assigning the appropriate segmentation labels to the final segmentation result, where segmentation maps disagree with each other.

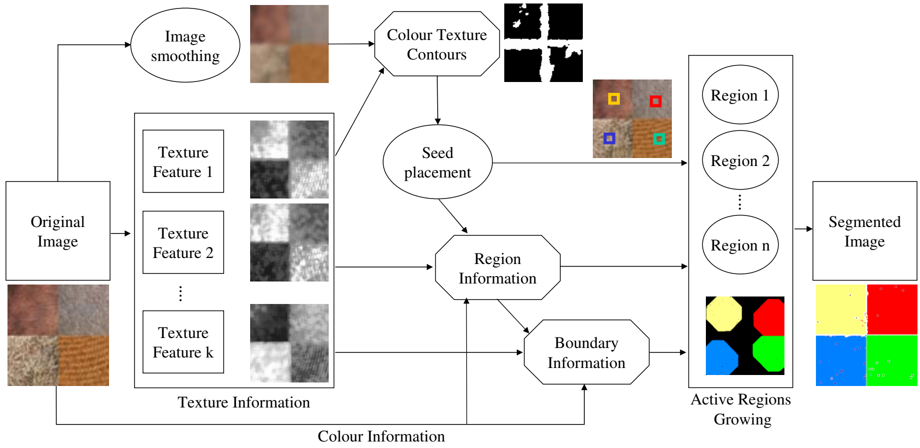

Fig. 1. Scheme of the proposed colour texture segmentation strategy.

It is only recently that attempts are being made to combine both aspects in a single method. Three alternatives to feature extraction for colour texture analysis appear to be most often used and they consist of: (1) processing each colour band separately by applying grey level texture analysis techniques [10,11], (2) deriving textural information from luminance plane along with pure chrominance features [12,13], and (3) deriving textural information from chromatic bands extracting correlation information across different bands [14,15,16,17].

Our proposal can be classified in the second approach, considering chromatic properties and texture features from the luminance, which facilitates a clear separation between colour and texture features.

2 Image Segmentation Strategy

As stated in our review work [5], the different integration strategies try to solve different problems that appear when simple approaches (region or boundary-based) are used separately. Hence, we consider that some of these strategies are perfectly complementary and it could be greatly attractive to fuse different strategies to perform the integration of region and boundary information. The fusion of several approaches will allow to tackle an important number of issues and to exploit at maximum the possibilities offered by each one. Hence, we propose an image segmentation method which combines the *guidance of seed placement*, the *control of decision criterion* and the *boundary refinement* approaches.

Our approach uses the perceptual edges of the image to adequately place a set of seeds in order to initialise the active regions. The knowledge extracted on these regions allows to define the region information and to extract accurate boundary information. Then, as these regions grow, they compete for the pixels of the image by using a decision criterion which ensures the homogeneity inside

(a) (b) (c)

Fig. 2. Perception of colour textures as homogeneous colour regions when are seen from a long distance. From original textured image (a), the image is progressively blurred until regions appear as homogeneous (b). Next, colour edges can be extracted (c).

the region and the presence of edges at its boundary. A scheme of the proposed strategy is shown in Figure 1. The inclusion of colour texture information into our initial segmentation proposal involves two major issues: 1) the extraction of perceptual edges, 2) the modelling of colour and texture of regions.

2.1 Initialisation: Perceptual Edges

To obtain a sample of each region large enough to statistically model its behaviour, initial seeds have to be placed completely inside the regions. Boundary information allows us to extract these positions in the "core" of regions by looking for places far away from contours.

Boundaries between colour texture regions, which are combination of colour edges and texture edges can be considered as perceptual edges, because a human has the ability to detect both ones. The problem of texture edge detection is considered as a classical edge detection scheme in the multidimensional set of k texture features which are used to represent the region characteristics [18]. Meanwhile, the extraction of colour boundaries implies a major difficulty since the use of an edge detector over a colour image produces the apparition of microedges inside a textured region. Our approach, is based on the perception of textures as homogeneous colour regions when they are seen from a long distance [16]. A smoothing process is progressively performed starting from the original image until textures looks homogeneous, as we would look the texture from far away. Then, the application of an edge detector allows to obtain the colour edges. Figure 2 shows the effect of smoothing a textured image; regions which were originally textured are appreciated as homogeneous colour regions.

The union of texture and colour edges provides the perceptual edges of the image. Nevertheless, due to the inherently non-local property of texture and the smoothing process performed, the result of this method are inaccurate and thick contours (see Figure 2.c). However, this information is enough to perform the seed placement in the "core" of regions, which allows to model the characteristics of regions.

2.2 Colour Texture Region Information

Colour in a textured region is by definition not homogenous and presents a very variable behaviour through different image regions. Hence, methods which implicitly assume the same shape for all the clusters in the space, are not able to handle the complexity of the real feature space [19]. Therefore, we focus our attention on density estimation from a non-parametric approach since these methods do not have embedded assumptions, and specifically we adopt the kernel estimation technique. Considering colour pixels inside seeds as a set of data points assumed to be a sample of region colour, density estimation techniques allow the construction of an estimate of the probability density function which describes the behaviour of colour in a region. Given n data points x_i, $i = 1, \ldots, n$ in the d-dimensional space R^d, the multivariate kernel density estimator with kernel $K_H(x)$ and a bandwidth parameter h, becomes the expression

$$\hat{f}(x) = \frac{1}{nh^d} \sum_{i=1}^{n} K_H(\frac{x - x_i}{h}) \tag{1}$$

which gives us the probability of a pixel to belong to a region considering colour properties, P_{R_c}, on the three-dimensional colour space. Note that in order to use only one bandwidth parameter $h > 0$ the metric of the feature space has to be Euclidean.

On the other hand, texture of each region R_i is modeled by a multivariate Gaussian distribution considering the set of k texture features extracted from the luminance image. Thus, the mean vector $\vec{\mu_i}$ and the covariance matrix Σ_i, which are initialised from the seeds, describe the texture homogeneity region behaviour. Therefore, the probability of a pixel of belonging to a region taking textural properties into account, P_{R_t}, is given by the probability density function of a multivariate Gaussian distribution.

Considering both properties together, colour and texture, the probability of a pixel j of belonging to a region R_i will be obtained considering the similarity of the colour pixel with the colour of the region, and the similarity of the texture around the pixel with the texture of the region. The combination of both terms gives the equation

$$P_R(j|R_i) = \beta P_{R_c}(j|R_i) + (1 - \beta) P_{R_t}(j|R_i) \tag{2}$$

where β weights the relative importance of colour and texture terms to evaluate the region information.

2.3 Colour Texture Boundary Information

It is well know that the extraction of boundary information for textured images is a very tougher task. On the other hand, human performance in localising texture edges is excellent, if (and only if) there is a larger patch of texture on each side available. Hence, as Will et al. [20] noted, texture model of the adjacent textures are required to enable precise localisation. The previous initialisation step of the regions model allows to dispose of this required knowledge and to extract accurate boundary information.

We shall consider that a pixel j constitutes a boundary between two adjacent regions, A and B, when the properties at both sides of the pixel are different and fit with the models of both regions. Textural and colour features are computed at both sides (referred as m and its opposite as n). Therefore, $P_R(m|A)$ is the probability that features obtained in the side m belong to region A, while $P_R(n|B)$ is the probability that the side n corresponds to region B. Hence, the probability that the considered pixel is boundary between A and B is equal to $P_R(m|A) \times P_R(n|B)$, which is maximum when j is exactly the edge between textures A and B because textures at both sides fit better with both models.

Four possible neighbourhood partitions (vertical, horizontal and two diagonals) are considered, similarly to the method of Paragios and Deriche [21]. Therefore, the corresponding probability of a pixel j to be boundary, $P_B(j)$, is the maximum probability obtained on the four possible partitions.

2.4 Active Region Growing

Recently the concept of active regions as a way to combine both region and boundary information has been introduced. Examples of this approach, called hybrid active regions, are the works of Paragios and Deriche [21], and Chakraborty et al. [22]. This model is a considerable extension on the active contour model since it incorporates region-based information with the aim of finding a partition where the interior and the exterior of the region preserve the desired image properties.

The goal of image segmentation is to partition the image into subregions with homogeneous properties in its interior and a high discontinuity with neighbouring regions in its boundary. With the aim of integrating both conditions, the global energy is defined with two basic terms. Boundary term measures the probability that boundary pixels are really edge pixels. Meanwhile, the region term measures the homogeneity in the interior of the regions by the probability that these pixels belong to each corresponding region. Some complementary definitions are required: let $\rho(R) = \{R_i : i\epsilon[0, N]\}$ be a partition of the image into $\{N + 1\}$ non-overlapping regions, where R_0 is the region corresponding to the background region. Let $\partial\rho(R) = \{\partial R_i : i\epsilon[1, N]\}$ be the region boundaries of the partition $\rho(R)$. The energy function is then defined as

$$E(\rho(R)) = (1 - \alpha) \sum_{i=1}^{N} - \log P_B(j : j\epsilon\partial R_i) + \alpha \sum_{i=0}^{N} - \log P_R(j : j\epsilon R_i|R_i)) \quad (3)$$

where α is a model parameter weighting both terms: boundary and region. This function is then optimised by a region competition algorithm [23] which takes the neighbouring pixels to the current region boundaries $\partial\rho(R)$ into account to determine the next movement. Specifically, a region aggregates a neighbouring pixel when this new classification decreases the energy of the segmentation. Intuitively, all regions begin to move and grow, competing for the pixels of the image until an energy minimum is reached. When the optimisation process finishes, if there is a background region R_0 which remains without being segmented, a new seed is placed in the core of the background and the energy minimisation starts again. This step allows a correct segmentation when a region was missed in the previous stage of initialisation. Furthermore, a final step merges adjacent regions if this causes the energy decrease.

3 Experimental Results

Before giving details of the formal method we used to evaluate our proposal, we would like to emphasize a feature that we believe is an important contribution of our proposal: the use of a combination of colour and texture properties. To illustrate this, Figure 3 shows a simple experiment which consists of the segmentation of a mosaic composed by four regions, each of which has a common property, colour or texture, with their adjacent regions. Specifically, each region has the same colour as its horizontal neighbouring region, while the vertical neighbouring region has the same texture. As is stated in the first two examples of Figure 3, the method allows the colour texture properties to be modelled and the four regions to be correctly segmented. On the other hand, we included in Figure 3 a third experiment which consists on the segmentation by using only colour information. Third image shows the smoothed version of the first mosaic image, and clearly illustrates that the original image contains only two colours. Therefore, the segmentation of the image using colour information, although different techniques can be used (considering a Gaussian distribution on the smoothed image, modelling using a mixture of Gaussians on the original image, or other techniques such as the kernel density estimation), will only allow us to identify two colour regions and it is not possible to distinguish regions with the same colour but different texture. As is stated, in some cases colour alone does not provide enough information to perform colour texture analysis, and in order to correctly describe the colour texture of a region, we need to consider not just the colour of pixels, but the relationships between them.

The described segmentation method can be performed over any set of textural features. The result of comparing the relative merits of the different types of features have been nonconclusive and an appropriated set of features has not emerged in all cases. For the experimental trials shown in this article we used the co-occurrence matrices proposed by Haralick et al. [24]. Two of the most typical features, contrast and homogeneity, are computed for distance 1 and for $0°$,$45°$,$90°$ and $135°$ orientations to constitute a 8-dimensional feature vector. Moreover, the (L^*, u^*, v^*) colour space has been chosen to model the colour.

In order to evaluate the proposed colour texture segmentation technique, we created 9 mosaic images by assembling 4 subimages of size 128×128 of textures from the VisTex natural scene collection by MIT (*http://www-white.media.mit.edu/vismod/imagery/VisionTexture/vistex.html*), which we have called from $M1$

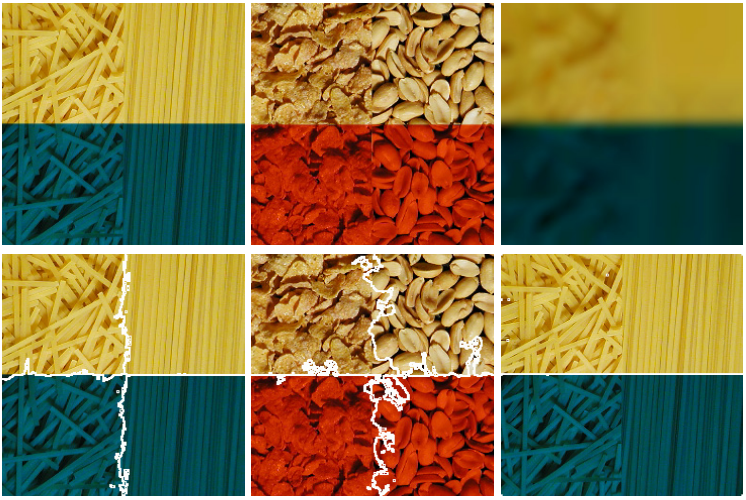

Fig. 3. Segmentation of 4 regions composed from two textures and two colours. First row shows the mosaic images. Second row shows the borders of segmented regions.

to $M9$. Furthermore, we added 3 mosaics $M10$, $M11$ and $M12$, provided by Dubuisson-Jolly and Gupta which were used to evaluate their proposal on colour texture segmentation described in [8]. A subset of colour texture mosaic images with obtained segmentation results is shown in Figure 4.

The evaluation of image segmentation is performed by comparing each result with its ground truth and recording the error. Specifically, we use both region-based and boundary-based performance evaluation schemes [25] to measure the quality of a segmentation. Region-based scheme evaluates the segmentation by measuring the percentage of not-correctly segmented pixels considering the segmentation as a multi-class classification problem. Meanwhile, boundary-based scheme evaluates the quality of the extracted region boundaries by measuring the distance from ground truth to the estimated boundary.

Images were processed by our segmentation algorithm using various set of parameter values for the weight of colour (parameter β) and texture information, as well as the relative relevance of region (parameter α) and boundary information in the segmentation process, and best results have been obtained with $\beta = 0.6$ and $\alpha = 0.75$. Note that a predominant role is given to colour and region information. Table 1 shows the quantitative evaluation of results obtained using this parameters setting over the set of mosaic images. Summarising, a mean error of 2.218% has been obtained in the region-based evaluation for the whole set of test images. While the mean error at the boundary has been of 0.841 pixels. Furthermore, our proposal obtained errors of 0.095%, 3.550% and 1.955% in the segmentation of $M10$, $M11$ and $M12$, respectively (see segmentation results of these mosaic images in second row of Figure 4), which can be compared to the

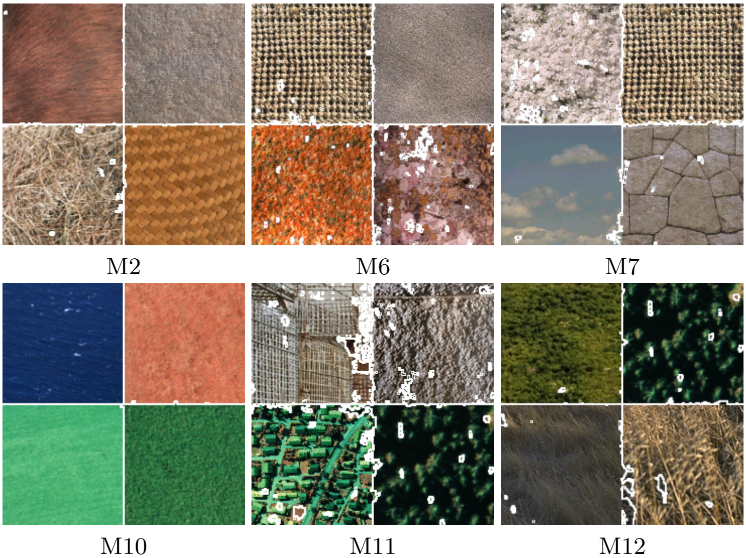

Fig. 4. Subset of mosaic colour texture images. Borders of segmented regions are drawn over original images.

segmentation results shown in the work Dubuisson-Jolly and Gupta [8]. Their proposal is a supervised segmentation algorithm based on the fusion of colour and texture segmentations obtained independently. Both segmentations are fused based on the confidence of the classifier in reaching a particular decision. In other words, the final classification of each pixel is based on the decision (from colour or texture) which has obtained a higher confidence. Our results have to be considered as very positive since they significantly improve colour texture segmentation results presented in [8].

Furthermore, the performance of our proposal for colour texture segmentation has been finally tested over a set of real images. Natural scenes predominate among these images, since nature is the most complex and rich source of colour and textures. Some colour texture segmentation results are shown in Figure 5. Meaningful regions in images are successfully detected and the usefulness of our proposal for colour texture segmentation is demonstrated. Furthermore, we want to emphasize some aspects related to the obtained results. See the last example of Figure 5 which shows the segmentation of a monkey among some leaves. The monkey is correctly segmented and, moreover, although the animal is absolutely black several parts of its skin are identified due to their different textural properties. Similar situations occur with other images in which animals are present. In the image with a leopard, region at neck which is not composed by typical spots of the animal, is detected and the same occurs with the lizard image in which the body of the animal, neck and belly are segmented as different regions. It is true that in these cases many of human would group all these regions to com-

Table 1. Region-based and boundary-based evaluation for the best results of colour texture segmentation over mosaic images ($\beta = 0.6$ and $\alpha = 0.75$).

	Region-based (% error)	Boundary-based (pixels distance)
M1	2.207	0.352
M2	0.280	0.145
M3	0.731	0.237
M4	2.375	0.588
M5	1.663	0.786
M6	2.352	0.341
M7	1.451	0.596
M8	6.344	1.774
M9	3.609	3.430
M10	0.095	0.028
M11	3.550	0.962
M12	1.955	0.852
Mean	2.218	0.841
Std	1.711	0.940

pose a single region related to the whole animal body. Nevertheless, this process of assembling is more related to the knowledge that we have about animals that to the basic process of segmentation. Hence, we believe that the segmentation performed by our proposal is correct as it distinguishes regions with different colour texture. The task of region grouping, if necessary, should be carried out by a posterior process which uses higher-level knowledge.

The correctness of boundaries obtained in these segmentations is also shown by the sketch of detected borders over original images. As has been pointed out, texture segmentation is specially difficult at boundaries and great errors are often produced at them. Hence, we want to note the accuracy of segmentations considering not only the correct detection of regions, but also the precise localisation of boundaries between adjacent textures.

4 Conclusions

A colour texture image segmentation strategy which integrates region and boundary information has been described. The algorithm uses the contours of the image in order to initialise, in unsupervised way, a set of active regions. Therefore, colour texture of regions is modelled by the conjunction of non-parametric techniques of kernel density estimation and classical texture features. Afterwards, region compete for the pixels optimising an energy function which takes both region and boundary information into account.

The method has been quantitatively evaluated on a set of mosaic images. Furthermore, results over real images riches in colour and texture are shown and

Fig. 5. Colour texture segmentation results on real images ($\beta = 0.6$ and $\alpha = 0.75$). Borders of segmented regions are drawn over original images.

analised. The results demonstrate the effectiveness of the proposed algorithm in estimating regions and their boundaries with high accuracy.

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