COLOUR SALIENCY-BASED PARAMETER OPTIMISATION FOR ADAPTIVE COLOUR SEGMENTATION

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ABSTRACT

In this paper we present a parameter optimisation procedure that is designed to automatically initialise the number of clusters and the initial colour prototypes required by data space partitioning techniques. The proposed optimisation approach involves a colour saliency measure used in conjunction with a SOM classification procedure. For evaluation purposes, we have integrated the proposed initialisation technique in an unsupervised colour segmentation scheme based on K-Means clustering and the evaluation has been carried out in the context of the unsupervised segmentation of natural images.

***Index Terms*—**Colour saliency, automatic initialisation, SOM, clustering, dominant colours, image segmentation.

1. INTRODUCTION

Data space partitioning algorithms have been widely applied to the segmentation of colour images due to their simplicity and low computational cost, but it is useful to note that their performance is critically influenced by two essential conditions: a) the improper initialization of the cluster centres that will force the algorithm to converge to local minima and produce erroneous results and b) the difficulty in selecting the optimal number of clusters (generally, this parameter is user defined). Consequently, the colour information is not optimally evaluated during the space partitioning process if the clustering algorithms are initialised on outliers or the number of clusters is incorrectly chosen. The existent initialisation techniques can be roughly classified into three categories: random, nested initialisation (repetition with different random selections) and histogram-based techniques. One major drawback of the existent procedures is that they are based on rigid architectures and as a result they are not capable of adapting to the colour image content. Also, it is useful to mention that for most of the initialisation schemes proposed to date the number of clusters parameter has to be manually selected. In this paper, we propose an unsupervised scheme that addresses the automatic initialisation problem associated with standard clustering algorithms, where the key element consists in the application of a colour saliency measure used in conjunction with a Self Organising Maps (SOM) classification procedure. The initialisation method detailed in this paper maximises the use of the colour information and has two essential advantages when compared to other initialisation techniques. The first is that the SOM network *adapts* to the colour image content. This is motivated by the fact that SOM is an unsupervised classification procedure that preserves the topology of the training set and is able to optimally sample the colour information present in the input image. The second advantage consists in the fact that the use of the colour saliency maximises the colour contrast and reduces the level of over-segmentation caused by uneven illumination, shadows and perspective and scale distortions.

The described unsupervised segmentation scheme is generic, robust and it has been evaluated on a large number of natural images. The experimental data indicates that the proposed algorithm can be successfully applied to accurately partition the image data into homogeneous perceptual regions with respect to the colour image content.

This paper is organised as follows. Section 2 defines the colour saliency measure. Section 3 details the procedure applied for the automatic selection of the clustering parameters. In Section 4 the experimental results are presented, while Section 5 concludes the paper.

2. THE COLOUR SALIENCY MEASURE

The colour saliency (*CS*) [1] is calculated for every cluster R_i ($i \in [1,k]$ where k is the number of clusters) of the segmented image and is defined as the average colour difference with respect to the 4–connected neighbouring (*N4*) regions. In equation (1), $NBP(R_i)$ is the total number of border pixels of the region R_i, $BP(R_i)$ is the set of pixels that defines the boundary of region R_i and $N_{diff\_N4}(x, y)$ represents the number of pixels in the 4-connected neighbourhood (*N4*) of the current pixel (x, y) that belong to a region different than R_i.

$$CS(R_i) = \frac{1}{NBP(R_i)} \sum_{(x,y)\in BP(R_i)} \frac{1}{N_{diff\_N4}(x,y)} \times \sum_{\{R_j(p,q)|(p,q)\in N4(x,y)\}} \left\| \overline{Col}(R_i) - \overline{Col}(R_j) \right\| \quad (1)$$

In equation (1), $\overline{Col}(R_i)$ defines the 3D vector that models the colour content within the region R_i, whose value is calculated as the mean of all pixels contained in the region R_i and (p, q) are the neighbouring pixels that belong to the regions R_j that are adjacent to the pixel located at coordinates (x, y). It can be noted that the saliency of the region R_i is calculated over all boundary pixels (x, y) and this measure is defined as the sum of Euclidian distances ($\|.\|$) between the pixels in the 4-connected neighbourhood that belong to the region R_i and those that belong to different regions. The sum of Euclidian distances in equation (1) is weighted by $N_{diff\_N4}(x, y)$ to avoid the local maxima generated by single pixel regions. The average image saliency S_{avg} is calculated as the mean of the saliency values obtained for all regions R_i ($i = 1,\ldots,k$) in the image.

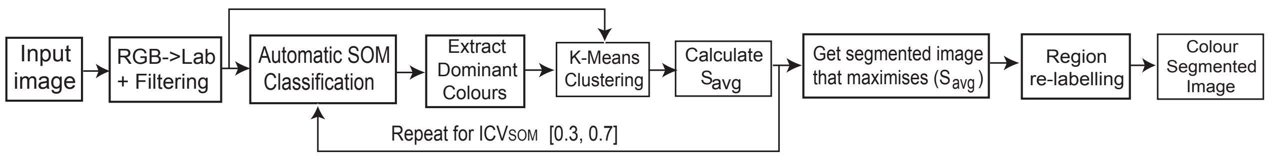


Figure 1. Overall computational scheme of the colour segmentation algorithm.

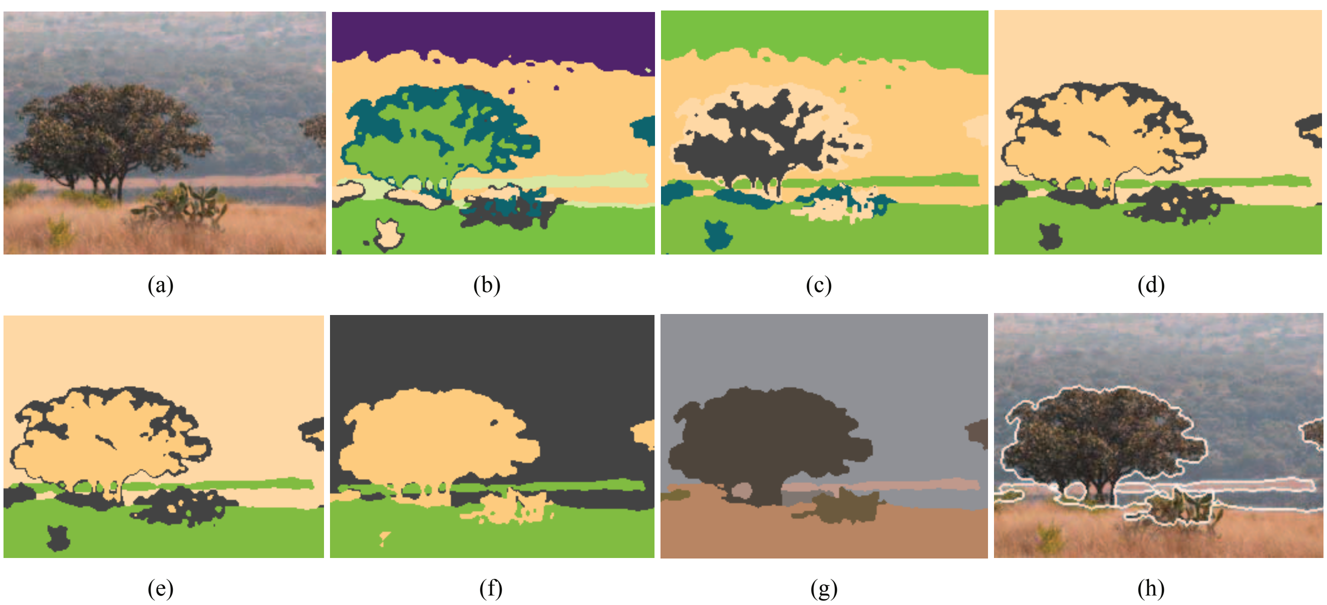
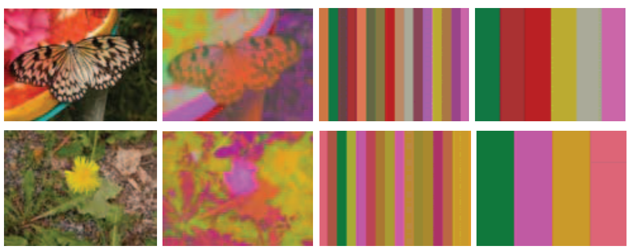


Figure 2. Colour image segmentation with parameter optimization. The cluster centres of the K-Means are automatically initialised using the colour seeds resulting from the SOM classification and the number of clusters k is calculated in agreement with an inter-cluster variability parameter (ICV_{SOM}). (a) Natural image with a high degree of complexity. (b) Clustered image 1 (for visualization purposes the clustered images are shown in pseudo colours), $ICV_{SOM} = 0.3$, $S_{avg} = 0.36$, number of clusters $k = 8$; (c) Clustered image 2, $ICV_{SOM} = 0.4$, $S_{avg} = 0.37$, $k = 6$; (d) Clustered image 3, $ICV_{SOM} = 0.5$, $S_{avg} = 0.40$, $k = 4$; (e) Clustered image 4, ICV_{SOM}=0.6, $S_{avg} = 0.40$, $k = 4$; (f) Clustered image 5, $ICV_{SOM} = 0.7$, $S_{avg} = 0.52$, $k = 3$. Image (f) generates the maximum S_{avg} (0.52) and the number of clusters $k = 3$. (g) The final colour segmented image resulting after the application of the post-processing step. (h) The final segmentation results where the object boundaries are over-imposed on the original image.

3. AUTOMATIC PARAMETER OPTIMISATION

The main components of the proposed algorithm are depicted in Figure 1. While our aim is the colour segmentation of natural images, the first component of the algorithm converts the input image from the RGB to the perceptually uniform CIE Lab colour representation. The converted image is subjected to a non-linear anisotropic diffusion filtering [2] in order to eliminate the image noise, weak textures and improve the local colour homogeneity. After the image is filtered, the number of clusters and the initial colour seeds (prototypes) are extracted using a two–stage automatic procedure. The first stage consists of a SOM-based classification [3, 4], where the input image vectors are trained in order to obtain a lower dimensional representation of the input image in the form of a feature map that maintains the topology within the training set. In our implementation, the SOM network is formed by 16 nodes which have been initialised with the histogram peaks of the CIE Lab filtered image that was subjected to colour quantisation [3]. This choice is motivated by the findings reported in several psychophysical studies where it has been demonstrated that 16 colours are sufficient to accurately sample the colour image content. In Figure 3c are illustrated the 16 initial dominant colours obtained after the SOM classification has been applied to two natural images.



(a) (b) (c) (d)

Figure 3. (a) Original images [5]. (b) CIE Lab filtered images. (c) SOM classification output (16 seeds). (d) Final dominant colours that are strongly related to the colour image content converted to CIE Lab representation.

During the second stage, the number of colour seeds is progressively reduced to their optimal value by evaluating a colour saliency measure in conjunction with an inter-cluster variability parameter (ICV_{SOM}). The pixels in the filtered Lab image (see Figure 3b) are mapped to the final weights (depicted in Figure 3c) of the cells in the SOM network based on the minimum Euclidian distance. Next, to each weight of the SOM network is assigned a confidence value which is calculated as the ratio between the variance within the cluster and the number of pixels in the cluster. The lower the confidence value, the more reliable the weight estimate is. Finally, the dominant colours resulting from the SOM map are iteratively merged until the Euclidean distance between any adjacent nodes in the network is higher than the ICV_{SOM} parameter. If this distance is smaller than ICV_{SOM}, the node that has the largest weighted variance (confidence value) is eliminated.

It has been quantitatively demonstrated in [1] that the maximisation of the border contrast (this implies the maximisation of the average saliency S_{avg}) leads to improved region stability. A high region stability in the context of image segmentation means that the resulting regions in the segmented data are not erroneously divided due to spurious texture or uneven illumination. Based on this observation, the optimal set of parameters is obtained for the clustered image where the average saliency measure is maximised.

To eliminate the supervision that involves the manual selection of the ICV_{SOM} parameter, in this paper we propose an approach that automatically determines this parameter with respect to the maximisation of a region saliency measure that samples the contrast between the neighbouring regions in the clustered image. In this regard, multiple clustered results for different values of the ICV_{SOM} parameter are generated and the optimal result is selected as the clustered image that maximises the average saliency measure (S_{avg}).

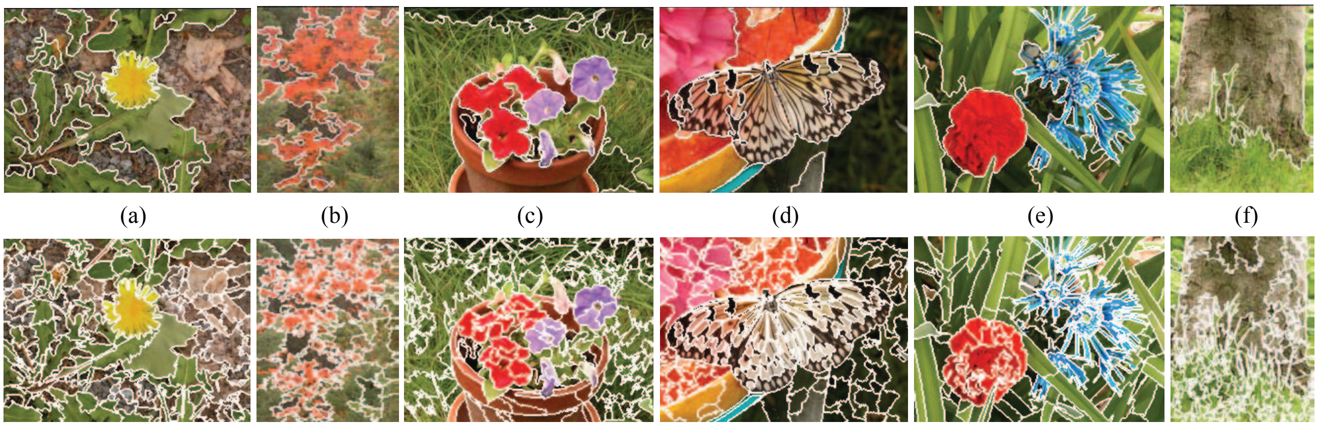
To improve the computational efficiency of our algorithm, the ICV_{SOM} parameter is varied in the interval [0.3, 0.7]. This range of values has been established based on experimentation since ICV_{SOM} values lower than 0.3 consistently leads to over-segmentation, while values larger than 0.7 produces under-segmented results. Hence, the calculation of the saliency measure for parameters outside the range [0.3, 0.7] will just increase the computational cost of the algorithm without any increase in performance.

The procedure that is applied to select the optimal ICV_{SOM} parameter can be summarised as follows:

1. Apply the SOM classification to the CIE Lab filtered image. Calculate the 16 colour seeds.
2. for (ICV_{SOM}=0.3; ICV_{SOM}<=0.7; ICV_{SOM}+0.1)
   {
   a) Reduce the number of colour seeds in agreement to the ICV_{SOM} and calculate the number of clusters k;
   b) Initialise the cluster centres and the number of clusters k for the K-Means scheme with parameters resulting from step 2a);
   c) Perform clustering on the CIE Lab filtered image;
   d) Compute the average colour saliency S_{avg} for the clustered image resulting from step 2c).
   }
3. Determine the clustered image that returns the maximum average saliency (S_{avg}).

The main advantage of the proposed initialisation technique when compared with existent methods consists in the fact that it can better adapt to the colour variations in the image content, as the feature space is better sampled by the weights of the SOM nodes that are updated in an iterative manner using competitive learning. In this fashion, the weights of the SOM network become more similar to the input image with the increase in the number of iterations. Also, the adaptive seed reduction based on saliency is strongly connected to the image content.

The step-by-step execution of the proposed parameter optimisation scheme is depicted in Figure 2, while in Figure 4 (1st row) a number of results are illustrated when our segmentation algorithm is applied to complex natural images. To illustrate the adaptive character of our algorithm, in the caption of Figure 4 are indicated the parameters automatically obtained after the maximisation of the S_{avg} value. We note that the optimal parameters vary significantly from image to image and this clearly indicates that the manual selection of the clustering parameters will return sub-optimal results. Although the clustered image that maximises the ICV_{SOM} parameter produces an accurate partition of the input image into perceptual regions, it also contains small spurious regions that are caused by the strong transitions in the colour information. To eliminate these undesired regions a post-processing step is applied. This step consists of an iterative re-labelling process that re-assigns the regions with less than 100 pixels to the neighbouring regions based on a colour similarity criterion in conjunction with the Euclidian distance.



(a) (b) (c) (d) (e) (f)

(g) (h) (i) (j) (k) (l)

Figure 4. Final segmentation results. (a) ICV_{SOM}=0.5, k=4; (b) ICV_{SOM}=0.3, k=3; (c) ICV_{SOM}=0.5, k=5; (d) ICV_{SOM}=0.5, k=6; (e) ICV_{SOM}=0.7, k=4. (f) ICV_{SOM}=0.4, k=3. (g-l) Mean Shift colour segmentation results. (Image size: 256×192).

4. EXPERIMENTAL RESULTS

We conducted the experimental results using the McGill colour image database [5]. The purpose of these experiments was to prove that the proposed parameter optimization method is accurate and the overall colour segmentation algorithm is suitable for the partitioning of natural images into perceptual regions. An important merit of our method consists in its ability to accurately segment the image objects characterised by colour inhomogeneities (that are often encountered in natural images) in an unsupervised manner. A number of experimental results are depicted in Figures 4 (a-f) where the segmentations of a set of complex images are illustrated. The aim of these experiments, as discussed in the previous section, was to evaluate the performance of our method to identify the optimal set of clustering parameters. For comparison purposes, in Figure 4 (2nd row) the segmentation results obtained using the EDISON implementation of Mean Shift [6] are also shown. In our tests, the Mean Shift parameters have been conservatively selected based on the guidelines provided in [6] and were set to the following default values: spatial bandwidth = 8, colour bandwidth = 6.5 and minimum region = 100 pixels. It can be observed that the proposed method (1st row) consistently outperforms the Mean Shift procedure.

The developed algorithm requires approximately 30 sec to process one image. Additional colour segmentation results when the proposed technique is applied to more than 200 natural images can be found by visiting the following web page: http://www.vsg.dcu.ie/code/ICIP_09_cipa.pdf

5. CONCLUSIONS

This paper has introduced a novel generic automatic clustering initialisation strategy where the optimal parameters (number of clusters and initial seeds) are determined using a saliency measure used in conjunction with a SOM classification algorithm. The proposed technique has been included in the development of an unsupervised colour segmentation algorithm and the experimental results proved that the optimal parameter selection is the key issue in obtaining an accurate partition of the input image into perceptual homogenous regions.

6. REFERENCES

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