# Topological Histogram Reduction Towards Colour Segmentation

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**Abstract.** One main process in Computer Vision is image segmentation as a tool to other visual tasks. Although there are many approaches to grey scale image segmentation, nowadays most of the digital images are colour images. This paper introduces a new method for colour image segmentation. We focus our work on a topological study of colour distribution, e.g., image histogram. We argue that this point of view bring us the possibility to find dominant colours by preserving the spatial coherence of the histogram. To achieve it, we find and extract ridges of the colour distribution and assign a unique colour at every ridge as a representative colour of an interest region. This method seems to be not affected by shadows in a wide range of tested images.

## 1 Introduction

Image segmentation is a useful tool, as a prior step, on quite computer vision tasks and, in this sense, an accurate and fast segmentation is required to work on real problems. On natural segmentation tasks, colour is a visual cue which humans use to differentiate between several objects on real world. Moreover, some methods reinforce this cue with the spatial coherence to distinguish between objects of an image. This paper proposes a method for colour image segmentation without the spatial coherence and its viability in real image segmentation. Although we are focused on the above conditions, the method can be extended to introduce spatial information.

On existing literature we can find some different methods focused on colour segmentation. A survey of these methods can be read on [1] and [2]. We are interested on the segmentation process as a topological analysis of the colour distribution. In this sense the existing method that best suit this model is the mean shift algorithm [3,4]. It is focused on finding regions with high density and join different local maxima by detecting saddle points. But, whereas mean shift works under a statistical point of view by finding the modes of a density function, we propose to find meaningful information under a topological point of view by taking a colour histogram as a 3-dimensional landscape. To achieve this topological segmentation, we propose a two step algorithm. First we apply a creaseness algorithm to enhance interest regions and discard regions of a low interest and, second, we propose an algorithm to find meaningful ridges from the relevant information in the creaseness values of the colour distribution. These

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ridges will represent the most representative colours, or dominant colours present in the image.

The paper is organized as follows: section 2 introduces the method and justifies the ridge concept; section 3 introduces our two-steps algorithm;. Section 4 shows some results, discussing the parameters in the operator, and conclusions and further work can be found on section 5.

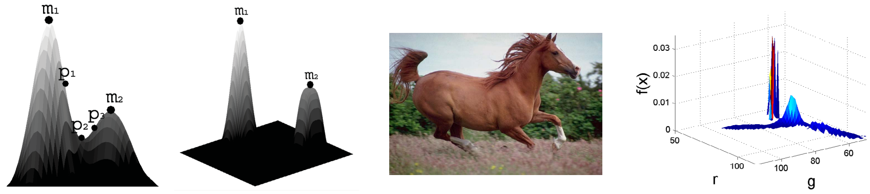
## 2 Method Outline

A grey-scale NxM image can be understood as an NxM landscape using grey values as height. What we propose is to extend this idea at our 3-dimensional space (colour histogram). The height value is explained, in our case, by the number of occurrences of every colour in the image, whereas red, green and blue in RGB space or hue, saturation and lightness on HSL, and so on, are the spatial position of each colour in the landscape. Theoretically, a surface with an homogeneous RGB colour should have just one RGB coordinate in its histogram. The problem resides in incident light and on the own acquisition devices which cause an elongated cloud (from shadows to saturation) in the RGB cube. What we expect is to extract the most representative colour inside this cloud, ideally, the original RGB value. We argue that inside this cloud exists a unique path with maximum height, e.g., a ridge, which summarizes the whole cloud and keeps the most representative colour.

The main idea of this ridge extraction is that ridges join different local maxima, e.g., local maxima which can be conceptually considered to belong to the same topological structure, and this idea avoids a possible over-segmentation and introduces the idea of spatial distribution coherence. Figures 1a and 1b illustrates with an ideal example this concept of distribution coherence that we include to achieve a good reduction of the RGB histogram. Figures 1c and 1d show a simplified 2D example (just showing normalized Red and Green channels) with a real image. In figure 1d we can guess a peak for every dominant colour in figure 1c. In other words, there exist, inside the histogram distribution, an intrinsic low-dimensional structure which summarizes the distribution preserving the spatial relationships between meaningful data. To find this structure we need, first, to spurn non representative data and, second, achieve a measurement that allow us to detect these possible highest paths without gaps due to local irregularities. In this sense, mean shift procedure has its own method for saddle point detection but has, as a main drawback, a high computational cost because it requires multiple initializations and some prior knowledge is needed to reduce the number of executions [5]. We propose to work on the topological definition of ridge.

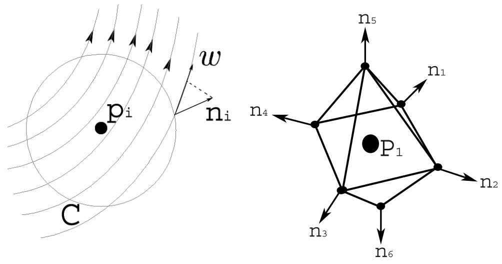
## 3 Topological Reduction of a Colour Distribution

As we told, we need to find a method to avoid the drawbacks related to acquisition conditions. In this sense, the operator proposed in [6], named *Multilocal*




a) b) c) d)

**Fig. 1.** Different possible shape interpretations for $m_1$ and $m_2$. Without $p_1$, $p_2$ and $p_3$, is not possible to distinguish between (a) and (b); (c) a real image and (d) its normalized Red-Green histogram, in spite of we really work with RGB histogram, but it is, obviously, impossible to show a 4-Dimensional space.




a) b)

**Fig. 2.** (a) Geometry involved in the definition of $k(p)$. A boundary C given by a neighbourhood of size $\sigma_1$. Divergence will be the dot product between vectors $\bar{w}$ and n.(b) Boundary C for a 3D ($d = 3$) regular grid according to the six nearest neighbours ($r = 6$).

*Creassenes Based on the Level-Set Extrinsic Curvatures Based on the Image Structural Tensor Field* (MLSEC-ST), in the following $\gamma(D, \sigma_1, \sigma_d)$ , gives us a useful tool. The creaseness analysis associates to every point the likelihood to be a ridge point and it is not affected by local irregularities. This operator assigns, to every point $p$, a creaseness value $k(p)$, by means of divergence calculation $Div(\overline{w}_p)$ between normalized gradient vector $\overline{w}_p$ and unit normal vectors $n_1, ..., n_r$ of the neighbourhood points. Multilocality, e.g., the fact because this operator is not affected by local irregularities, is achieved by computing divergence , not just on a point $p$, but taking into account gradient vectors of a neighbourhood of size $\sigma_i$. Figure 2a shows a graphical example. We define the creaseness operator on a d-dimensional space with r-connectivity neighbourhood (see figure 2b) as:

$$k(p) = -Div(\overline{w}_p) = -\frac{d}{r}\sum_{k=1}^{r} \overline{w}_k^t(\sigma_i) \cdot n_k \qquad (1)$$

Finally to improve results, the Structural Tensor (ST) study allows us to get a coarse measure of the degree of anisotropy to assign low creaseness values at zones of low interest like flat regions. ST performs an eigensystem calculation of gradient vectors on the neighbourhood with a Gaussian kernel of standard deviation $\sigma_d$ and, as a result, enhances dominant directions of landscape. Then we can summarize first step of our algorithm as follows:

$$C(D) = \gamma(D, \sigma_1, \sigma_d). \tag{2}$$

Where $D$ is a given distribution; in this case, $D$ is the image histogram.

Once we apply the creaseness operator, we have enhanced the meaningful information of $D$, without gaps due to local irregularities, on a new distribution $C$. This information can be collected by a ridge extraction procedure as a good descriptor of $D$ and its spatial structure. In this sense, if we directly extract ridges on $D$, local irregularities will break ridges and it will cause different interpretations where, if we maintain spatial coherence, there should be only one.

### 3.1 The Ridge Extraction Algorithm

A good ridge characterization on a gray-scale image domain is introduced in [7] and a comparison between main algorithms is introduced in [8] where the use of $\gamma(D, \sigma_1, \sigma_d)$ is proposed.

Our method for ridge extraction is focused on a topological point of view. If we want to cross a landscape, we consider that the way with lowest cost is a ridge. When we walk across a ridge, we observe that mountain falls on both sides. In other words, a ridge occurs where there is a local maximum in one direction or, symmetrically, when a zero crossing on the gradient image occurs. It can be translated, in discrete domain, as follows: $x$ is a ridge point if is higher than all its neighbours except one point $x'$ which is, in fact, a neighbour belonging to the ridge. Hence, in a 3-dimensional $r, g, b$ space with 26-connectivity neighbourhood, we define $R(C) = \{r_1, ..., r_n\}$, the collection of ridge points, as:

$$R(C) = \{x \in C \mid \mu(x, C) < 2\} \tag{3}$$

$$\mu(x, C) = \sharp \{y \in neighbourhood(x) \mid C(y) \geq C(x)\} \tag{4}$$

This ridge operator is defined and discussed in [9]. But due to discrete domain, this approach has some drawbacks as figure 3a illustrates. The main problem is that ridges are broken and it entail an over-segmented image.

We propose a new definition of ridge operator on the discrete domain, by beginning in points which are not affected by discretization, e.g., local maxima (figure 3b). Hence, as initialization step, we find local maxima on C, $\lambda(C)$ as follows:

$$\lambda(C) = \{x \in C \mid \mu(x, C) = 0\} \tag{5}$$

Then, we just have to follow ridges starting on $\lambda(C)$ points to avoid discretization problems. It means that we follow a ridge from a local maximum until its

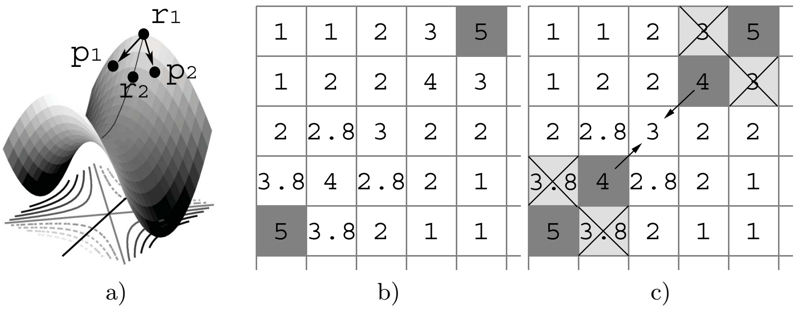



**Fig. 3.** (a) an example of discretization: $r_1$ and $r_2$ are ridge points. Theoretically $r_2$ should be higher than all neighbours except $r_1$, but the discreatization process takes $p_1$ and $p_2$ as points higher than $r_2$. (b),(c) A synthetic 2D creaseness image: (b) Local maxima found in gray, e.g., $\lambda(C)$. (c) Second step: Applying $\mathcal{R}(\mathcal{C})$ points labeled with 4 become ridge points. The next step should be to go to light grey squares labeled with 3.8, but we do not take these into account because belong to $\Omega$. Then, we achieve a straight ridge. On the next step just the central point of the square can be a ridge point.

ending. Let $neigh(x) = \{n_1, ..., n_{26}\}$ be the neighbourhood of a point $x$. We also define $\Omega(x, n_j) = \{\omega_1, ..., \omega_r\}$ ,$j = 1..26$, as the set containing common neighbours between $x$ and one of its neighbours $n_j$; having $r = 16$ if $dist(x, n_j) = 1$, $r = 10$ if $dist(x, n_j) = \sqrt{2}$ and $r = 6$ if $dist(x, n_j) = \sqrt{3}$. Where $dist(x, n_j)$ is the euclidean distance. Notice that neither $x$ nor $n_j$ are included in $\Omega$. Then, we define the ridge points in a creaseness image $C$, as:

$$\lambda_z(C) = \lambda_{z-1}(C) \bigcup \{n \in neigh(l) \mid l \in \lambda_{z-1}(C), \mu'(l, n) = 0\} (C) \qquad (6)$$

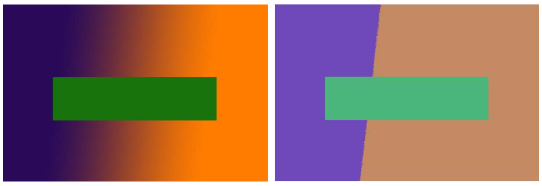
$$\mu'(x, n_j) = \sharp \{y \in \Omega(x, n_j) \mid C(y) \geq C(n_j)\} \qquad (7)$$

Then, we add iteratively new points to $\lambda(C)$. This process stops, in the pth step, when ridge arrives on a flat region, achieving a new image with as many ridges as mountains in $C$. Hence:

$$\mathcal{R}(\mathcal{C}) = \lambda_p(C) \qquad (8)$$

Once we find a new ridge point $n_j$, we will not to take into account points belonging to $\Omega(x, n_j)$ as a possible ridge points on a further steps, in order to avoid discretization problems and achieve a ridge of width equal to 1 as figure 3b and 3c illustrates.

As we told before, every ridge $r_j$ summarizes its mountain, lets said, $M_j$. In a final step, we assign to every point $x$ belonging to $M_j$ the average colour of $r_j$. It implies that we must know the borders of $M_j$. At present, we do an approximation by making a rgb cube partition with a Voronoi calculus from ridges.



a) b)

**Fig. 4.** Synthetic example: (a) Original image (b) Segmented Image

## 4 Experimental Results

With our topological colour segmentation we have achieve promising results. Prior experimental results demonstrate that our operator is not affected by shadows in a wide range of digital images. Furthermore, whole process works at quasi-real time since it is able to process seven images per second on a standard PC.

When we deal with colour distributions we must choose a correct colour representation between all well-known colour spaces. The most used colour space is the RGB (red, green, blue) space, basically due to acquisition and display devices which usually work with this three chromatic coordinates. Some other possibilities would be perceptual colour spaces as CIELUV or CIELAB, [10] and other device dependent spaces such as HSL or NRGB [11]. Since our topological distribution reduction is a generic operator and is not focused on a concrete colour space, we do not care on which space we perform its behavior analysis. As for experimental use, we test it on RGB, CIELAB and normalized RGB spaces. Figure 4 shows an example with a synthetic RGB image.

In order to evaluate the possibilities of our method, we used real indoor and outdoor images, what allows us to better appreciate how exactly ridges are found, because histogram of a synthetic image is not enough illustrative. Figue 5 shows an example of the whole procedure. First, we take an RGB image (figure 5a) and its histogram (figure 5b). Ridges found, and final partition of RGB cube, can be seen on figure 5c. We can observe that ridges maintain the structure of the original colour distribution. Finally, figure 5d shows the segmented image.

Figure 6a and 6b illustrates an example with a CIELAB image. The main problem is that perceptual colour spaces require a calibrated image for a good conversion from another space. Thus, to convert non calibrated images to a perceptual colour space will imply some errors, and its viability should be evaluated. What does not mean that RGB is the best representation for colour segmentation. Actually, RGB has two important shortcomings. First, the nonlinearity, second, a high correlation between its components, and third, is not a perceptually uniform space, e.g., relative distances between colours do not reflect the perceptual differences. HSV is a linear transformation from RGB, thus, inherits its drawbacks. Finally, figures 6c and 6d show an example with normalized RGB which tries to avoid the effects related to incident light.

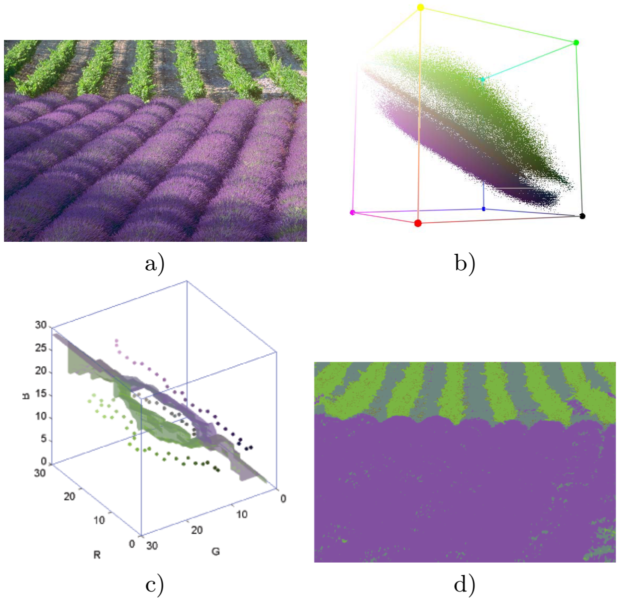



**Fig. 5.** Real image example:(a)Original outdoor image.(b) RGB histogram of a). (c) Ridges found and RGB cube final partition. (d) Image segmented.

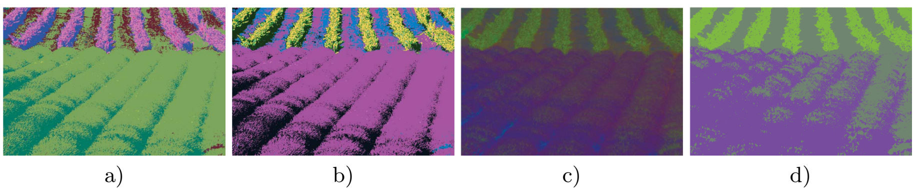



**Fig. 6.** Real image example: (a)Original outdoor CIELAB image and (b) its segmentation. (c)NRGB image and (d) its segmentation.

On these experiments the behavior of $\sigma_i$ and $\sigma_d$ has been checked, It seems that results are robust against slight changes of $\sigma_1$ and $\sigma_d$. In fact, results of figures 4 and 5 have the same $\sigma_i$ and $\sigma_d$ values.

## 5 Conclusions

Our topological colour segmentation method attain good results on a wide range of images even without using spatial coherence and is conceptually easy and computationally efficient.

Nevertheless there are some things that must be improved. First, the RGB cube partitioning is, right now, just an approximation of the best solution because delimitation between mountains is not correctly found. It means that, in some images, we incorrectly assign the colour of some pixels. To solve this problem we can do a classification of every coordinate of the histogram or, at least, a further study of creaseness distribution, to find where exactly the borders of any mountain are. Finally, we must study other colour spaces and the characteristics of the segmentation, or what exactly implies to do a segmentation in each of these spaces.

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