Multiscale Color Edge Detection by a Fuzzy Approach

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Abstract

Color edge detection has been normally based on the vector extension of classical (scalar) derivative operators. This extension has been done either by the independent processing of each color component and aggregation of the partial results or by the synthesis of a special color space, featuring a single highly relevant component. These approaches fail to embed any visual perception information. This paper proposes the use of a perceptually relevant dissimilarity measure, based on a fuzzy color model and on a spatial symmetry color spread index as the basis of a color edge detector.

Introduction

The edge detection problem is an instance of the more general image segmentation problem. Although the image segmentation process has been divided into region-oriented segmentation and edge-oriented segmentation, the two approaches are dual. Their ultimate goal is to partition the image in mutually exclusive, non-overlapping, uniform and meaningful areas, characterized by the set of points of their interior (region-oriented segmentation) or by the set of boundary points between neighboring regions (edge-oriented segmentation).

Basically, all edge detection operators rely on the computation of an edge intensity map, which is further thresholded in order to obtain a binary edge map. The edge intensity map must provide important values for the pixels that are on the boundaries of uniform regions. In the case of gray-level images, an edge is characterized by a discontinuity (or variation) of the image intensity. Further models assume various edge categories, identified according to edge orientation (e.g. the compass operators), edge strength (step, roof, or impulse), or edge geometry (isolated point, line, or corner as proposed by Frei and Chen). Traditionally, edge identification is performed by derivative measures (gradient or Laplacian) and thus implemented by linear filtering structures. The derivative is computed along a set of fixed orientation (as in the case of the compass operators) or along the orientation of the strongest intensity variation. This approach (and the related topographical or morphological methods) is mainly based on the analytical interpretation of the image as a function (or surface).

Color Edge Detection - Classical Approaches

The computation of the edge intensity map is based on the determination of the local color non-uniformity, and thus on the deduction of the locally extreme colors. The definition of color extremeness with respect to a set of given colors implies the introduction of an ordering relation in the color space, whether or not the actual color difference is specifically using the color ranking. As pointed out by Barnett[1] there is no natural, simple and direct extension of the ordering (or ranking) concept in higher dimensions. Several sub-ordering principles have been considered for practical implementation[1]: marginal ordering, reduced ordering, conditional ordering and partial ordering (the latter without edge detection implementations).

The early approaches to color edge detection usually were extensions of scalar edge detectors. Nevatia[4] proposed the use of a Hueckel-like edge operator, searching separately the edges in different components of the color image (intensity, normalized components, luminance-chrominance). Robinson[5] extended the compass operators with the Kirsch mask for composite color representation components (such as brightness). Scharkanski and Venetsanopoulos[7] proposed a similar approach using extended Prewitt masks and LOG (Laplacian of Gaussian) operators and aggregating their responses from the red, green, and blue components. Trahanias and Venetsanopoulos[8,9] proposed several edge detector operators based on the concept of directional processing of color - meaning that the difference between colors is measured by the angle of their corresponding vectors and color vectors are ranked according to the aggregate sum of their inter-vector angles.

The use of hypercomplex numbers (which are similar to a complex number, but with three imaginary parts) proposed by Sangwine and Thornton[6] for the representation of colors opens the perspective of using frequency domain processing techniques.

The Fuzzy Multiscale Color Edge Detection Algorithm

The proposed algorithm is based on the idea of constructing an edge intensity map that does not results from an explicit color difference measure or a color extremeness decision. The color information is processed by mapping each color into a fuzzy set; the edge intensity map results from the evaluation of the spatial distribution of the fuzzy membership degrees of the colors selected within each analysis window.

In the case of color images, color attributes and color differences play a particularly important role in the perception of object boundaries. The process of measuring color differences must be designed to maintain a balance between the computed and the perceived difference. Still, the simple use of standardized color representations (like the Lab) does not explain the similar perception and the visual confusion of certain colors. We propose to deal with this factors in the framework of a fuzzy color representation.

We will thus associate to each color \textbf{c}, that usually is a point in the three-dimensional color gamut $\boldsymbol{C}$ (determined by the color space representation), a Lukasiewicz function, $\mu_c : \boldsymbol{C} \rightarrow [0,1]$ that measures the membership degree of any color $\boldsymbol{c}'$ from $\boldsymbol{C}$ within the class "color $\boldsymbol{c}$" (a similar approach was used in Ref. 2 in the framework of gray-level image processing). Thus, $\mu_c(\boldsymbol{c}')$ is a scalar within [0,1] that expresses how similar is the color $\boldsymbol{c}'$ to the color $\boldsymbol{c}$. The analytical definition of the function μ_c must take into account the natural perception and thus μ_c must be decreasing with respect to the inter-color distance $d(\boldsymbol{c}, \boldsymbol{c}')$ (regardless the definition of that distance). A typical model is the one proposed by Haffner[3] (in the framework of comparison of color histograms for image indexing):

$$\mu_{\mathbf{c}}(\mathbf{c}') = \exp\left(-\sigma\left(\frac{d(\mathbf{c},\mathbf{c}')}{d_{\max}}\right)^2\right) \qquad (1)$$

with $d_{\max} = \max d(\boldsymbol{c}, \boldsymbol{c}')$ for all $\boldsymbol{c}, \boldsymbol{c}' \in \boldsymbol{C}$.

The tuning parameter σ in equation (1) allows to consider color similarity functions that are more or less localized, and thus to modify the inter-color confusion. We may also notice that the expression in (1) implicitly depends on the maximal dimension of the color gamut (through $d_{\max}$) and thus takes into account the color quantization. Once the color quantization is chosen and thus $d_{\max}$ is determined, the tuning parameter σ can be easily related to the imposed similarity degree $\mu 1$ associated to a color lying at an unitary distance (i.e. $d(\boldsymbol{c}, \boldsymbol{c}')=1$) from the target color $\boldsymbol{c}$, by $\sigma = -d^2_{\max}\ln\mu 1$. Other models are equal possible.[10]

Our goal is to define a scalar that can globally characterize the second order statistical distribution of pixels having a same color within a spatial neighborhood. Thus, this index will enable the distinction between edge pixels, corner pixels and coherent pixels (placed in uniform color regions). For each image pixel we consider a squared, centered neighborhood. Within this neighborhood, all pixels having the same color as the color of the central pixel are marked as ones, all other pixels being marked as null. For the resulting binary mask we compute the number of one-valued pixels within several symmetrical distributed mask slices, quarters of the squared analysis window, rotated by 90 degrees (Q_1 - Q_4) or by 45 degrees (Q_1 - Q_8). We may also note that all the slices of the mask contain its central pixel. Let we denote by s_i the sum of values within each mask slice Q_i. If all the 4 or 8 numbers s_i are about the same, it means that the central pixel belongs to an area of relative symmetrical spatial distribution of its color. If there are dissimilarities between the s_i numbers, the central pixel is characterized by a color that is unevenly distributed in its neighborhood. We define the color symmetry spread index S as (2):

$$S = \frac{\max_i s_i - \min_i s_i}{\sum_i s_i} \qquad (2)$$

It can be easily noticed that the S index is a range-to-mean ratio and measures the uniformity of the set s_i. The index has higher values for corners and for edge points than for the near-uniform points.

The same approach can be used within the fuzzy color model approach. The mask used for the computation of the S index is not longer binary, but will consist of numbers within [0,1], the degree of similarity between the color of the considered pixel and the color of central pixel (the pixel "under test"). The same mask partitioning procedures and definitions for s_i and S are used and the index values have the same relevance with respect to the edge/ non-edge pixel classification.

Eventually, the complete color edge detection algorithm can be summarized as follows:

1. choose the visual resolution level by imposing a tuning parameter of the color similarity function
2. for each pixel (i, j) within the image, select its neighbors $(i+k, j+l)$, according to a square, centered analysis window
3. for the selected pixels compute their color similarity $\mu_{f(i,\ j)}(f(i+k,\ j+l))$ with respect to the color of the central pixel, $f(i, j)$
4. compute the spatial symmetry color spread index, S and copy its value at location (i, j) in the edge intensity map
5. threshold the edge intensity map in order to obtain a binary edge or corner map; the segmentation threshold can be determined by any usual method (such as the cumulative histogram thresholding).

Experiments

We used the classical "lena" and "peppers" images for several tests of color edge detection, using the proposed approach. There are two main factors that influence the obtained edge intensity map: the tuning parameter $\mu 1$ (or σ) of the color similarity function (that determines the shape of the fuzzy set associated to the colors) and the size of the analysis window used for the computation of the symmetry index S. For the first tests we use the same color quantization and analysis window size (5 x 5) and we vary the tuning parameter of the color similarity function $\mu 1$, between 0 and 1. If $\mu 1=0$ the color model is crisp: $\mu_c(\boldsymbol{c}')=1$ if and only if $\boldsymbol{c}=\boldsymbol{c}'$, all other values being null. If $\mu1 \rightarrow 1$, a higher inter-color confusion is introduced; at the limit, all colors are considered similar. Figures 1 a) through 1 c) show the edge intensity maps that result for various values of $\mu1$. Figures 2 a) through 2 c) show the edge intensity maps that result for various sizes of the analysis window. The results show that the increase of the $\mu1$ parameter brings a simplification of the extracted contours, only the most visual dominant edges being recovered for $\mu1$ close to 1. Indeed, the increase of $\mu1$ produces a higher color confusion, which is equivalent to an image blurring produced by an increased viewing distance of the scene. We claim that the observed behavior with respect to the $\mu1$ color similarity parameter can be declared as multiscale.

Conclusions

The proposed algorithm is based on the idea of constructing an edge intensity map that does not results from an explicit color difference measure or a color extremeness decision. The color information is processed by mapping each color into a fuzzy set; the edge intensity map results from the evaluation of the spatial distribution of the fuzzy membership degrees of the colors selected within each analysis window. The color spatial distribution is condensed into the spatial symmetry color spread index, that enables to dissociate edge and corner pixels from coherent pixels. A multiscale behavior is obtained by the continuos variation of a tuning parameter of the color fuzzy model.

Noise invariance can be obtained by the increase of the size of the analysis window used for the computation of the spatial symmetry color spread index.

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Biography

Dr. Constantin Vertan is a lecturer with the "Politehnica" University of Bucuresti, Romania and an invited professor at the University of Poitiers, France. His main research interests are color image processing and analysis, content-based image retrieval and the applications of fuzzy logic in image processing.

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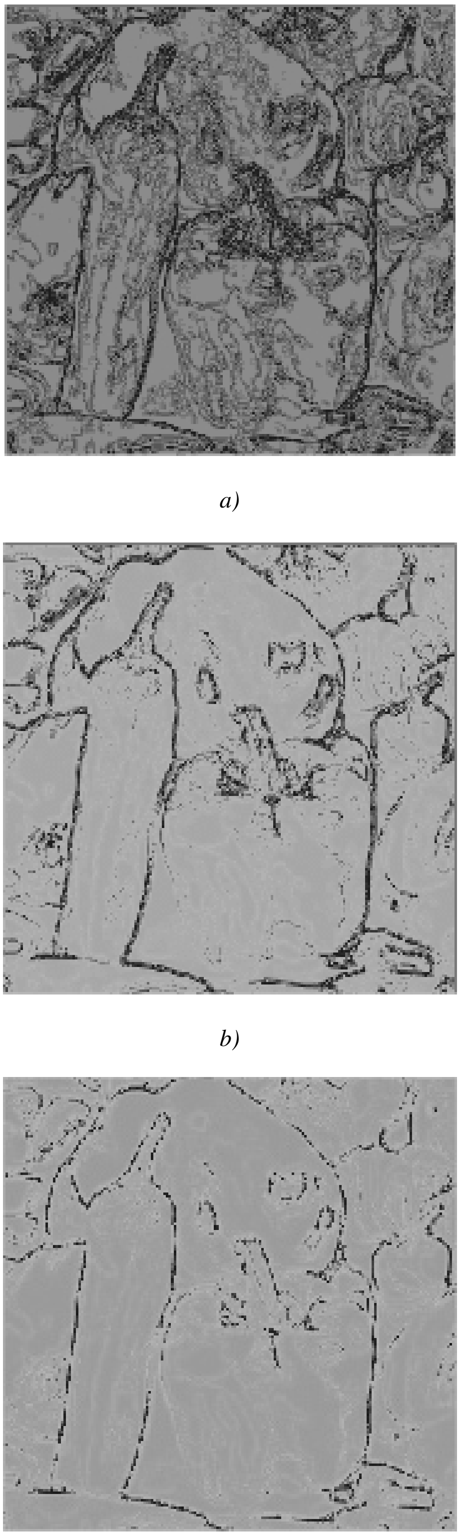
a)

b)

c)

Figure 1. Edge intensity maps (false colored) extracted from the original true-color image "lena" by the proposed algorithm using the same color quantization and analysis window size (5 x 5) and varying the tuning parameter of the color similarity function µ1: a) 0.25 ; b) 0.75 ; c) 0.95.}



a)

b)

c)

Figure 2. Edge intensity maps (false colored) extracted from the original true-color image "peppers" by the proposed algorithm using the same color quantization and tuning parameter of the color similarity function µ1=0.25 varying the analysis window size: a) 3 x 3 ; b) 5 x 5 ; c) 7 x 7.