# A ROBUST NONLINEAR SEGMENT-EDGE FINDER

*Mark Mertens, Hichem Sahli and Jan Cornelis*

Vrije Universiteit Brussel, Department of Electronics, IRIS laboratory
Pleinlaan,2 B-1050 Brussel
contact email: mjmerten@etro.vub.ac.be

## ABSTRACT

In this paper we describe a nonlinear criterion designed for the detection of changes ("edges") in signal or image properties in a framework that we call the **distinction evidence method**. It was introduced as a generic feature extraction tool for image modeling. We show its capabilities when applying it to segmentation, texture border finding and object correlation problems.

## 1. INTRODUCTION

In a previous article [1] we considered the criterion in an edge finding framework and analyzed its accuracy and robustness as an edge detector with criteria equivalent to Canny's [2] localization and SNR. In this article we will make the link to region segmentation applications, since it is often desirable that region segmentation and edge finding segmentation give similar results, which is not trivial because they are differently formulated. Since our decision criterion uses concepts from both worlds, it will be a good candidate for consistent edge finding-segmentation. We will derive our criterion from a correlation point of view, which will lead to further interesting applications when specific shapes have to be extracted. We will also comment on the criterion's nonlinearity and its use in texture applications. A single method capable of handling all the mentioned problems is useful because real images contain a mixture of all the cases, and a simple generic strategy is also highly desirable in adaptive applications. We will primarily focus upon the principles and will sometimes drop illustrating results, because of the limited length of the paper.

## 2. GENERAL DESCRIPTION OF THE DISTINCTION EVIDENCE METHOD

To see if the image properties change, we will compare a region with a nearby region. For the simplest feature extraction we will consider only the histogram of the regions and not the geometrical position of the particular pixel values. In the case of homogeneity, the histograms in the two regions are similar to each other. If there is a significant property difference, this will manifest itself in the difference of the histograms of the two regions. In the case where spatial correlation information is important, a simple preprocessing will suffice to incorporate the necessary information in the histograms of the pretreated image regions.

The distinction evidence method typically runs as follows:

1. Generate two sample sets in supposedly different regions. E.g. for a boundary polygonalization we postulate (predict) the existence of a linear edge segment, called separator $\hat{\mathbf{S}}$ (shown dashed in Figure 1), characterized by a starting point $(x_0, y_0)$, an associated angle $\alpha$ and length $l$. Around this separator we construct 2 rectangular sampling regions with width $w$ (Figure 2).

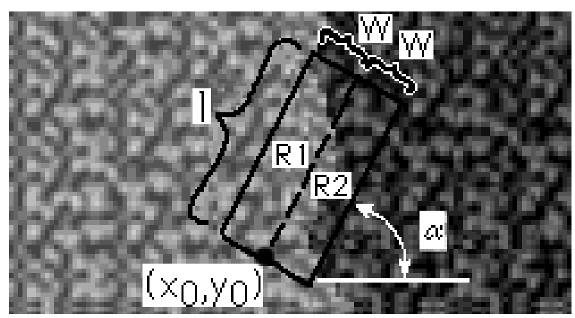


Figure 1: Evaluation of goodness of fit of separator $\hat{\mathbf{S}}$ to a local boundary

2. Calculate the decision or gain value associated with this separator $\hat{\mathbf{S}}$ by means of formula (1).

$$G(\hat{\mathbf{S}}, i(T)) = \frac{\sum_{i \in N(T)} \left| C_i^{R_1(\hat{\mathbf{S}})} - C_i^{R_2(\hat{\mathbf{S}})} \right|}{2lw} \quad (1)$$

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The decision value or *gain* $G$ is the sum (over all "color" values $i \in N(T)$ ) of the absolute values of the differences between the number of pixels with color $i$ in $R_1$ (namely $C_i^{R_1(\hat{\mathbf{S}})}$) and in $R_2$ (namely $C_i^{R_2(\hat{\mathbf{S}})}$). The $i$'s are appropriately chosen by defining a set of *input* thresholds T depending on the application, from which we can calculate the class $i$ of a gray value $g$ by means of $T_j \leq g < T_{j+1} \Rightarrow i(g) = i$. In adaptive applications these thresholds could be calculated during runtime, but we don't consider such applications in this paper. We use the name color for any numerical value: e.g. the image may contain the result of some texture feature preprocessing, upon which we calculate the gain function. The assumed "objects" (or segments) on either side are hence characterized by means of their histogram, and the difference of these histograms (1 minus *histogram overlap*) is calculated as a measure of the difference of the object regions $R_1$ and $R_2$ (Figure 2), rather than just the difference between weighted average gray levels, as in most classical edge detection techniques.

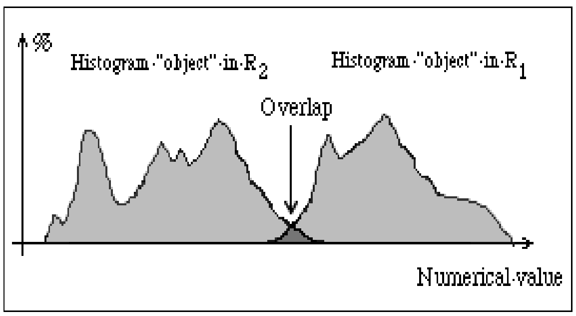


Figure 2: Statistical interpretation of the decision criterion $G$.

The histogram overlap can be intrinsic due to the particular object boundary and noise, or because of a mislocalization of our predicted separator $\hat{\mathbf{S}}$.

We have used formula (1) in an *edge validator*, which yields a 1 or 0 for the existence of the edge under the associated postulates $(\hat{\mathbf{S}}, w)$. In practice depending on the gain outcome, which will be somewhere between 0 and 1, we will make the interpretations { clear detection, clear evidence, doubtful evidence, clearly no feature }, with *output* thresholds (not to be confused with the input thresholds) that we choose corresponding to the particular application.

3. Generate a new prediction in such a way that in the end we will have found all the edges. We can use a classical scan or a more advanced search strategy.

## 3. DEVELOPMENT OF THE GAIN FUNCTION FROM A CORRELATION POINT OF VIEW

Binary matching, or in other words verifying whether two binary patterns are the same, is a simple problem, for which the normalized match index [4] was developed as a powerful tool. If we only reward the matches and do not punish the mismatches (formula (2)), the result can vary between 0 and 1, and if we match pixels whatever their position (i.e. $N^{fit}$ just counts the number of paired say black pixels on either side), we can use formula (2) for the edge detection strategy explained in paragraph 2 in case we only work on binary images.

$$C = \frac{N^{fit}}{N^{fit} + N^{nonfit}} \ ; \quad G = 1 - C \tag{2}$$

The analog concept for gray value images is the correlation. If for a certain pixel more bitplane values match, the partial pixel correlation value will relatively be higher. However the sensitivity of the correlation value to image pixel value changes, as compared to the correlation template values, is low when the pixel values are high, and vice versa. We would like another extension to gray value images, which keeps the idea of binary acceptance/rejection counting. The basic idea is to map the gray value image to a binary image, by labeling the pixels as [Non Changed, Changed] in the edge detection paradigm and [LeftObject, RightObject] in the segmentation paradigm. We therefore introduce the concept of majority colors as colors that characterize better a certain object since there are more pixels with this color in the object region (e.g. left rectangle) than in the other region. We can then in each sampling region identify three types of pixels: majority matching ($I$), majority excess ($II$) and minority matching pixels ($III$). We then define the match as:

$$C = \frac{N^I + N^{III}}{N^{tot}} = \frac{N^{tot} - N^{II}}{N^{tot}} \quad (= 1 - \frac{excess}{N^{tot}})$$

and the difference (gain) as:

$$G = \frac{excess}{N^{tot}} = \frac{\sum_{i \in N} |N_i^L - N_i^R|}{N^{tot}} \tag{3}$$

where the $N_i$ in formula (3) are the $C_i$ of formula (1) .

## 4. NONLINEARITY

Even for the simplest application, which just takes the difference of the histograms in a binary image, the absolute values make the criterion(1) nonlinear. Since the criterion(1) is blind to the exact numerical "color" values, we investigate the appearance of the nonlinearity when we add measurements on different parts of the image together.

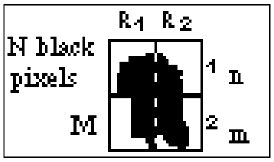


Figure 3: Composition of a larger sampling set from two smaller ones.

Suppose that a larger sampling window consists of the windows 1 and 2 on top of each other as depicted in Figure 3, with respective areas $A_1$ and $A_2$. In the left half of window 1 there are $N$ black pixels and in the right $n$, etc. We calculate the partial gains $G_1$ in the upper and $G_2$ in the lower pair of rectangles. When the majority of black pixels is not in the same half of windows 1 and 2, the linear formula (4) yields a different result than formula (1) due to the absolute difference in formula (1).

$$\begin{aligned} G &= \frac{(N+M-n-m)}{A_1+A_2} = \frac{(N-n)+(M-m)}{A_1+A_2} \\ &= \frac{A_1G_1+A_2G_2}{A_1+A_2} \end{aligned} \qquad (4)$$

Of course when several "colors" are sampled, linearity will almost certainly be violated.

The nonlinearity has some interesting aspects. Our basic conjecture is that to model images, which are formed by highly nonlinear processes, we need a nonlinearity in the first level detection algorithm. Nonlinearity is necessary to clearly separate the objects from the background. An edge validator can only be robust, i.e. give a correct edge validation irrespective of the particular edge details in the image, if it is nonlinear.

The above described nonlinearity means that the detector validates naturally the edges on all scales in scale space (where $w$ and also $l$ determine the scale), always yielding perfect localization for clear edges, i.e. edges that are not curved. Our criterion forms a good basis for a general edge definition, which is considered to be a fundamental problem in image processing, since the lower values of the gain can be mathematically expressed in terms of histogram overlap, edge jaggedness and also parameter misestimation. The price to pay for the nonlinearity is that our experiments to develop a Hough transform-like evidence collection scheme, to estimate bigger line segment parameters from measurements on many small segments along the bigger line, didn't give very satisfactory results on small scales.

The fact that the gain is normalized means that we can suppress the less relevant, noisy local maxima. A normalized measure is perfect for the parameter estimation in modeling, since we know we have to converge to a definable high $G$ value of nearly 1. Having a normalized value means that we do not necessarily need to look for local maxima (of $G(x_0, y_0, \alpha, l)$), but we can make statements on the basis of a single evaluation. This opens the door to more advanced flexible edge finding strategies, like random or object driven image search or connectionist systems. E.g. the normalization can be used to tackle the multiple optima problem when using a genetic algorithm search strategy.

Another useful property is the non zero contribution of the noise, which of course always contains some edginess. This led us to a principle where we add noise with predetermined properties for an optimal detection in vaguely situated regions of the image where we suspect certain boundaries to be present, to enhance the detection of the boundaries as in *stochastic resonance* [3]. Suppose that in a medical application we know more or less where the wall of say a heart should be, but that it is not imaged clearly. We might then add some noisy pixels in that region to force it to become visible. Since it is not an easy thing to do we don't know whether this concept will evolve from principle to practice.

## 5. USE AS AN IMAGE SEGMENTATION TOOL

In our framework the distinction between the edge finding and segmentation approach is very subtle, since in both cases we calculate edges. The first difference lies in the way we manipulate the bins that collect the histogram counts (Figure 2). For segmentation we will specify meaningful *input* thresholds, so that all gray values between two such thresholds belong to the same class $i$, whereas for edge detection we will blindly specify a number of equidistant threshold values. The second difference lies in the generation of the global segments.

In a noisy image there will be many different color values, so small sampling regions in a homogeneous region have a considerable probability of generating large gain values. One solution is to enlarge the sampling regions, another is to reduce the number of colors/bins. This can be done globally by quantizing more coarsely.

We will retain the larger amplitude edges and destroy the smaller ones. Another possibility is to reduce the number of colors locally, retaining in each two region sample set e.g. 4 values. In a homogeneous region we will then find more or less equal numbers of all colors in both regions, whereas near an edge the colors should be more organized geometrically. Although we call the equidistant thresholds approach the edge finding approach, it can also lead to a segmented image of course. The more meaningful thresholds for the segmentation approach can be obtained as follows. In a stamp detection application e.g., we can investigate the distribution of the colors of the white border of stamps for a number of typical stamps and select based upon this data a number of thresholds pinpointing this border histogram. In the example of Figure 5, we contrasted the typical dark pupil pixels with the lighter eye white "background" pixels, by putting them in different histogram bins.

The distinction evidence method can detect at least three types of edge important to (human) vision:

1 Large intensity changes can be quickly found in a coarse quantization.

2 Very small differences in a geometrically precise sampling setup can be detected (e.g. a dark truck against the black background at night).

3 Significant values, e.g. outliers, specular reflections, can be detected by putting a threshold just around their extremal values.

Even large amounts of interference typically occurring in real life image processing applications, like e.g. raindrops on the camera, need not be disturbing in a good experimental setup. We can neglect these colors and accept as clear edge evidence the lower gain values resulting from the fewer true object pixels between the raindrop pixels. Figure 4 shows the result of a segmentation setup, where we used three equidistant global thresholds, quantizing the peppers image to three colors.

## 6. ROBUST CORRELATION

If we also take the sampling region shapes into account, matching them with the desired object structures, we get a robust correlation approach. In the example of Figure 5 the sampling regions were created in a pupil/iris ($R_1$) and eye white ($R_2$) shape, and the input thresholds were now chosen for optimal separation of the eye object values to find the two eyes of Lena. Remark that in this case the separator $\hat{\mathbf{S}}$ is not a line segment. In a more general case we would have to test

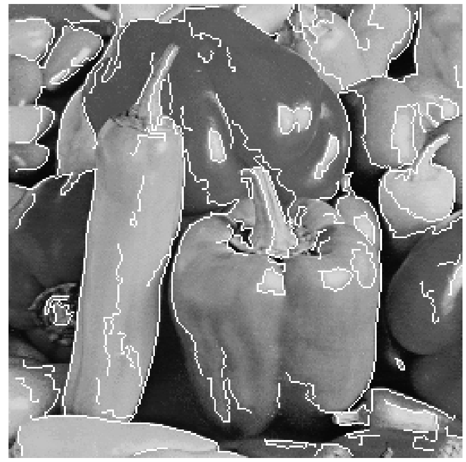

Figure 4: Example of a segmentation application on the peppers image.

different sizes, shapes and threshold combinations. But we need only calculate e.g. a set of semicircular mask shapes with different radii, while always evaluating the same gain function on the obtained sample sets. As we can see in Figure 5 both eyes, and only the eyes, give a clear detection maximum.

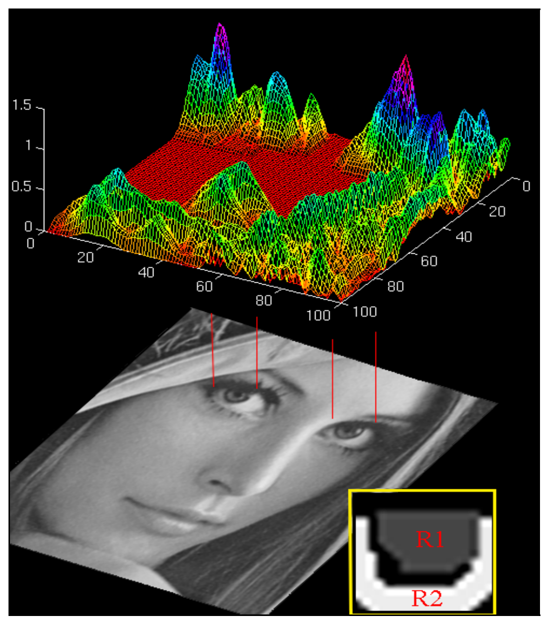


Figure 5: Output of eye detection and geometric shape of sampling regions (inlay).

## 7. TEXTURE DISCRIMINATION

The distinction evidence method can be used as an alternative texture segmentation method directly on the image or as a post processing step on images preconditioned by other texture techniques. Remember that after preprocessing the resulting image might still be too complex a gray value image to be analyzed by a simple technique like e.g. thresholding. In the direct applications two groups of methods can be used. The first just uses the rectangular setup of Figure 1, where the length and width of the sampling rectangles can further be chosen according to the texel scale. The gain function can then detect changes e.g. in variance, skewness... or more complex histogram properties. If necessary special combinations of the bin values can also be calculated. The second method applies sampling masks optimized to match the texel shapes. We show a few examples of the rectangular sampling method (Figure 6), showing that the maximum gain clearly corresponds to the correct texture boundary. We have done experiments on 88 texture squares, with all kinds of texture, compared under exactly the same non optimized conditions, resulting in 79.5% of the edges being detected, 86.5% of which were correctly localized.

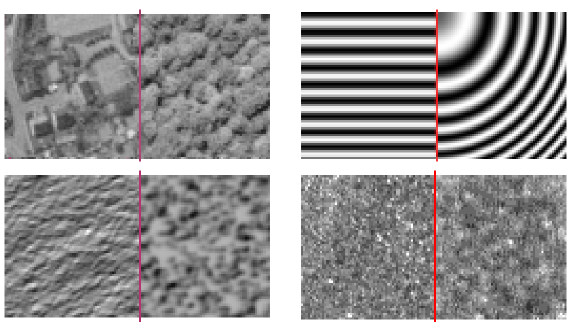

Figure 6: Detection of the boundary between two textures .

## 8. CONCLUSION

We have developed a new distribution free edge decision criterion, that bridges the gap between edge finding and segmentation. It can be used as a robust and versatile feature extraction tool, which seems difficult to achieve when using exact functional forms depending on the numerical values of the pixels. Although in many cases the simple postulates like e.g. white Gaussian noise are maintainable, and averaging strategies are hard to beat, we looked for a criterion that is not hampered too much by violations of these postulates. In particular, the exact noise distribution as well as its autocorrelation do not matter, leading to almost no edge interference (see e.g. the texture experiments). On the other hand we can measure a lot of edge types, characterized by other parameter changes than the average gray value, and having more information in the histogram makes our method more robust and versatile than methods which are based purely on the average, which is not a particularly useful descriptor for complex distributions. Geometrically the strategy is very simple due to the fact that it samples the pixels on equal basis, as we could see from the ease with which a particular sampling shape is chosen (e.g. the toothed boundary pattern of a stamp). The reader should compare our gain function with the complicated detection formula based on the Canny strategy used by Oakley and Shann [5], just for the extraction of arc segments. For binary images (or well separated histograms) the criterion is analogous to the Prewitt edge finder, from which one can theoretically develop the other filters like Canny's and Shen/Castan's [6].

We think that the idea can shed more light on several theoretical aspects of image processing. Moreover we expect that due to its versatility, the method can be optimized to tackle many applications, and we especially suspect it to be useful in adaptive strategies. Since the criterion is computationally simple, fast hardware could be developed.

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