Smooth Contour Detection

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today

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Introduction

We propose an unsupervised method for detecting smooth contours in digital images. Following the a-contrario approach, we first define the conditions where contours should not be detected: soft gradient regions contaminated with noise. This leads to a validation method based on a statistical test on edge operators similar to the ones used by Marr-Hildreth classic method that produces "meaningful" edges. The latter provides a natural link to the biological mechanisms of vision. This validation combined with heuristics based on the work of Canny and Devernay, results in an effective algorithm producing sub-pixel accuracy. The single free parameter of the method is the scale of the analysis.

Motivation

Figure: An image and various examples of regions that a human will eventually mark as contours: change in intensity, difference in texture, apparent contours created by gestaltic laws as closure or good continuation.

Motivation

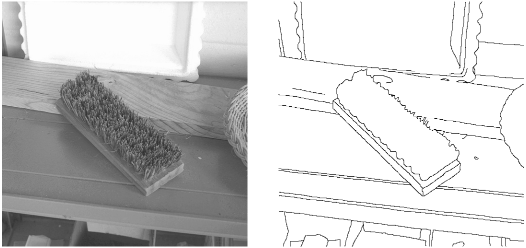

Figure: An image and the set of contours a human see on it. Image extracted from the RuG database

Motivation

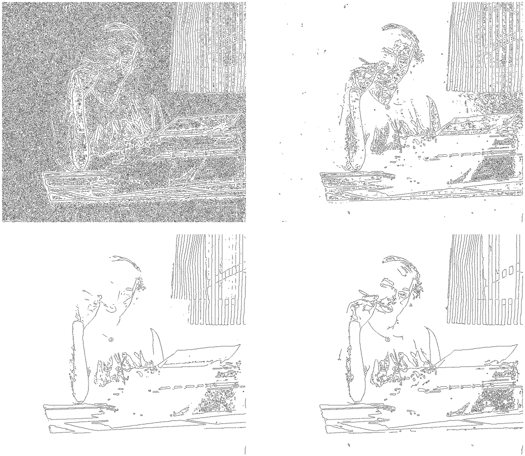

Figure: Different threshold values for the Non Maximal Suppression step of the Canny filter: 0.1, 2, 10 and 2 threshold with hysteresis with values 2 and 10

Figure: Canny edge detector with different thresholds in the hysteresis step of the algorithm. (a) $Th_{low} = 1$ and $Th_{high} = 5$, (b) $Th_{low} = 1$ and $Th_{high} = 20$, (c) $Th_{low=2}$ and $Th_{high} = 10$, (d) $Th_{low=2}$ and $Th_{high=20}$. Note how all the set of parameters give some non meaningful contours.

Basic idea

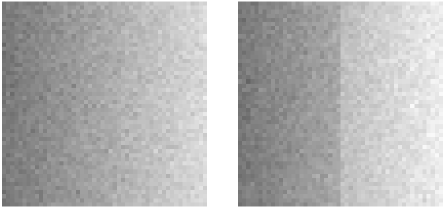

Figure: Two noisy images, one containing an edge.

Basic idea

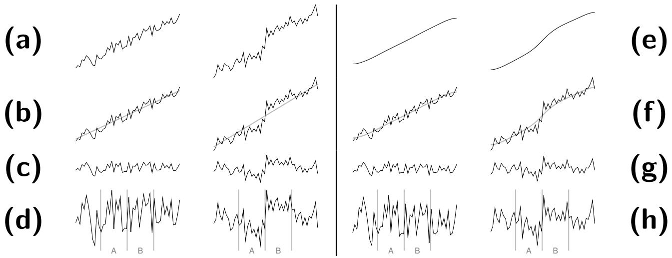

Figure: Main ideas with 1D graylevel profiles. **(a)** horizontal graylevel profiles from the images in Figure 5. **(b)** Profiles superposed to their best fitting line. **(c)** Difference between the profiles and their best fitting line. **(d)** Vertically scaled versions of (c), with zones A and B of the edge operator indicated. **(e)** Same profiles as in (a) but filtered with a Gaussian filter. **(f)** Superposition of the profiles and their Gaussian filtered versions. **(g)** Difference between the profiles and their corresponding Gaussian filtered versions. **(h)** Vertically scaled versions of (g). Edges are detected when values in B are consistently higher than the ones in A.

Basic Idea

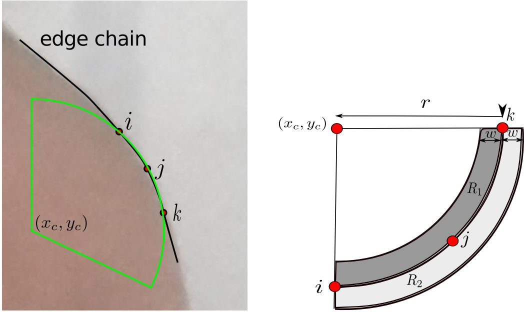

Figure: Given a chunk of edge chain with initial point i, middle point j and last point k define an arch a of length len, radius r and center (x_c, y_c). Two neighbouring regions are created R_1 and R_2 by two arcs of same center as a and radius $r - w$ and $r + w$ respectively. The number of points in region R_1 is n_1 and in region R_2 is n_2.

Validation

To validate a meaningful arc two tests are applied: (i) the distance between the points in the curve and the estimated arc accounts for the "smooth" part and (ii) the $NFA(a)$ gives an idea of the meaningfulness of that piece of curve in terms of edge that separates two regions with significant difference in their gray level values if $NFA(a) < \epsilon$. We want to have the expectation of detect less than one meaningful arc in a noise image of dimensions X and Y so we fix $\epsilon = 1$ once and for all.

Validation

The Mann Whitney U test counts de number of times that a pixel of region R_2 has a greater gray level than a pixel of region R_1. For two given regions of size n_1 and n_2 with no statistical difference between their intensity levels there is a value u of this statistic. We can normalize the measured statistic u for a particular distribution of gray levels in a region in order to have a normal distribution, using the estimated mean μ and variance σ for those regions by $z = \frac{U-\mu}{\sigma}$. In order to estimate the probability $P_{H_0}(U \geq u)$ of observing an statistics U greater or equal than u under the a-contrario hypothesis H_0, we use the error function $erf()$:

$$P_{H_0}(U \geq u) = \sqrt{1 - erf(z/\sqrt{2})}$$

NFA

In order to define a Number of False Alarms measurement associated to an edge arch we need, besides the probability given by the Mann Whitney U Test, a number of tests, in this case the number of arcs that can be defined in a given image. We define the number of test in the following way: the number of arc centres that can be defined in an image is the number of points $X \cdot Y$, the number of radius of those circles which is roughly $\sqrt{X \cdot Y}$, and the number of arcs defined by that circle. An approximation of that number of arcs is the area of the circle $\pi \cdot (len \div 2)^2$. Finally, we test num_w widths for the neighbouring regions in each arch.

$$N_{tests} = \sqrt{XY} \cdot X \cdot Y \cdot \pi \cdot (len \div 2)^2 \cdot num_w \qquad (1)$$

The NFA of an arc a is then:

$$NFA(a) = N_{tests} \cdot P_{H_0}[U \geq u] \qquad (2)$$

Results

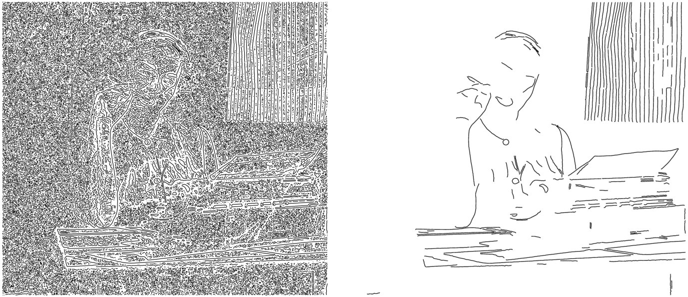

Figure: Left: the output of the Devernay edge detector algorithm on the image of 1. Are marked all the pixels that are maximal in a local neighbourhood without the application of a threshold on the output of the gradient estimation. Right: the output of the proposed Smooth Contours detection algorithm.

Results

Figure: An image.

Results

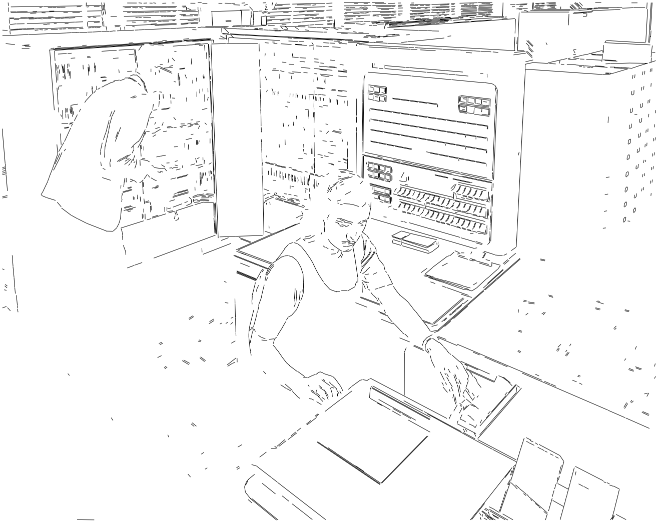

Figure: LSD detections

Results

Figure: Smooth curve detections.