

Edge Detection on a Computational Budget: A Sub-linear Time Approach

Boaz Nadler

The Weizmann Institute of Science

Joint work with
Inbal Horev, Ronen Basri, Meirav Galun (WIS)
and
Ery Arias-Castro (UCSD)



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this work is part of ICRI project

Understanding and Utilizing Natural Image Statistics

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Understanding and Utilizing Natural Image Statistics

Team Members:

- ▶ Yair Weiss, Hebrew University
- ▶ Miki Elad, Technion
- ▶ Anat Levin, Weizmann Institute
- ▶ Boaz Nadler, Weizmann Institute

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Main Goals: Better understand natural image statistics and how they can be used in analysis and design of improved algorithms for image processing and computer vision.

Edge Detection

A fundamental task in low level image processing.

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well studied problem, many algorithms

well understood theory.

Our Focus:

Edge detection in **very noisy** 2D images and 3D video

Motivation(s):

1. Images at non-ideal conditions: poor lighting, fog, rain, night.
2. surveillance applications
3. Real time object tracking in 3D video

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Image Prior:

- Interested in long straight edges.

Example: Powerlines



Traditional Edge Detection Algorithms

Typical Approach: Detect edges from *local* image gradients.

Example: Canny Edge Detector, complexity $O(n^2)$

linear in total number of image pixels
fast, suitable for real-time

Limitation: Does not work well at low SNR

Example: Canny, run-time 2.5sec



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Cannot detect faint powerlines of second tower

Modern Sophisticated Methods

[Brandt, Galun, Basri, 07]

[Alpert, Galun, Nadler, Basri, 10]

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- (Theoretically) Efficient multiscale algorithms, robust to noise

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Run time: $O(\text{min})$ for large images, $O(\text{hours})$ for video.

Example: Straight Segment Detector, run-time 19min



Challenge: Sublinear Time Edge Detection

Goal: Devise **extremely fast** edge detection algorithm, that is also **robust to noise**.

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Questions:

- Statistical: which edge strengths can one detect vs. α ?
- Computational: optimal sampling scheme ?
- Practical: *sub-linear* time algorithm ?

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In various applications:

Large and very noisy images (1000×1000 pixels or more)
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Examples:

- Battery of Cell-Phone
- Solar Power of distant surveillance camera
- Mobile Robots

Problem Setup

Observe $n \times n$ noisy image

$$I = I_0 + \xi$$

I_0 - noise free original image

ξ - additive noise, assume ξ_{ij} are i.i.d. zero mean, variance σ^2 .

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Assumptions:

- Image I_0 contains *few* edges (sparsity).
- Edges of interest are straight and sufficiently long.

Given sub-linear budget:

- 1) what are *optimal* sampling schemes ?
- 2) what are fundamental limitations on sub-linear edge detection ?
- 3) what is the tradeoff between *statistical accuracy* and *computational complexity* ?

Optimal Sublinear Edge Detection

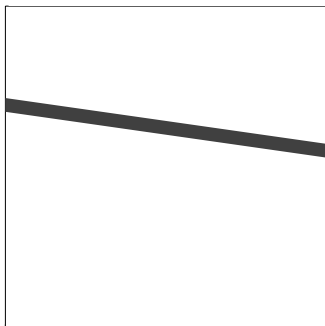
Consider set of possible images:

$$\mathcal{I} = \{I \text{ contains only noise or one long fiber plus noise}\}$$

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Theorem: Assume number of observed pixels is s and s/n is integer. Then,

- i) any optimal sampling scheme observes exactly s/n pixels per row.
- ii) sampling s/n whole columns is an optimal scheme.

Statistical Accuracy vs. Computational Complexity

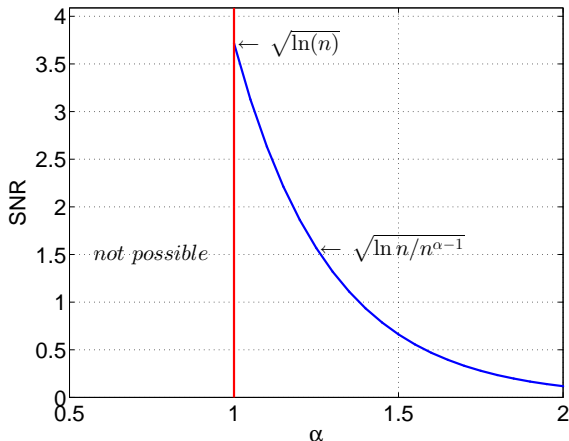
Definition: Edge SNR = edge contrast / noise level.

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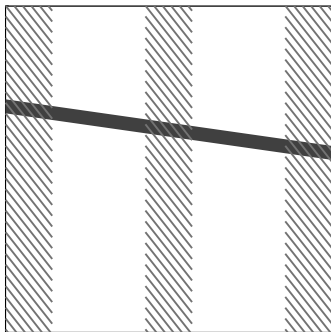
Theorem: At complexity $O(n^\alpha)$, with $\alpha \geq 1$,

$$\text{SNR} > \sqrt{\ln n / n^{\alpha-1}}$$



Sublinear Edge Detection Algorithm

Key Idea: Sample fraction of image strips

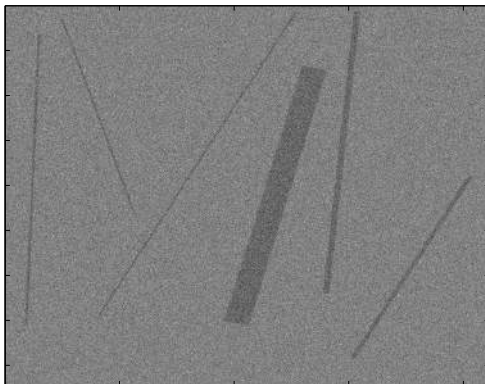


Sublinear Edge: Postprocessing

- Non-maximal suppression
- Edge Validation
- Edge Localization

Example

NOISY IMAGE, SNR=1



Example

CANNY

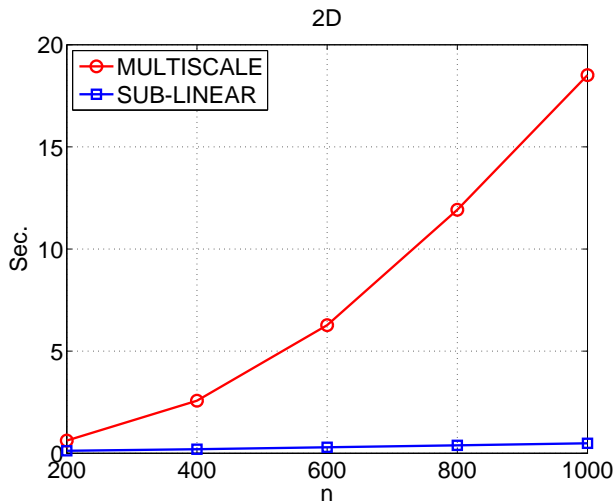


SUB-LINEAR



Run Time / 2-D Images

Actual results / Matlab / Preliminary Implementation:



Sublinear Time Edge Detection, run-time few seconds



- Theory: Better understanding of statistical vs. computational tradeoff for other problems in image analysis, computer vision, and "big-data" in general.
- Develop Robust Real-Time Algorithm in 2-D (beyond proof-of-concept).
- Development of theory and sub-linear algorithm in 3-D.
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Thank You / The End