

A Contrario Edge Detection with Edgelets

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Edge detection methods

- ▶ Canny filter [Canny, 1986], Deriche filter [Deriche, 1987]:
“good detection, good localisation, and minimal response”.
- ▶ Multi-resolution methods.
- ▶ Non linear methods.
- ▶ A contrario framework.

Outline

- 1 A contrario detection
 - Principle
 - Desolneux edge detection

- 2 Our contribution: introducing edgelets in the AC framework
 - General methodology
 - Features estimation
 - Combining several features
 - Results

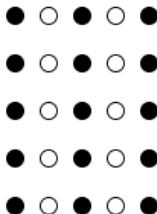
- 3 Conclusion

Introduction

- ▶ Proposed by Agnès Desolneux, Lionel Moisan and Jean-Michel Morel (1999).
- ▶ First, a statistical method of detection of *relevant* geometric structures:
 - ▶ Alignments [Desolneux, Moisan, Morel, 2000],
 - ▶ **Contours** [Desolneux, Moisan, Morel, 2001],
 - ▶ Segments [Grompone, Jakubowicz, Morel, Randall, 2008], ...
- ▶ Then, extended to many other applications in vision:
 - ▶ Shape Recognition [Musé, Sur, Cao, Gousseau, 2006],
 - ▶ Motion [Veit, Cao, Bouthemy, 2006],
 - ▶ Clustering [Cao, Delon, Desolneux, Musé, Sur, 2007],
 - ▶ Objects matching [Burrus, Bernard, Jolion, 2008],
 - ▶ Matching of local features [Rabin, Delon, Gousseau, 2009],
 - ▶ Stereovision [Sabater, Almansa, Morel, 2011], ...

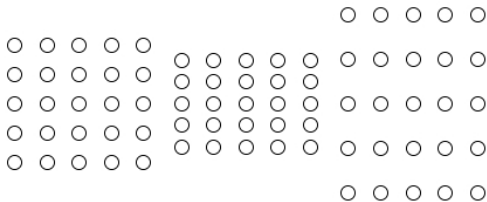
What's a relevant geometric structure?

- ▶ Gestalt theory: underline the importance of perceptual grouping for human visual perception.
- ▶ A non-exhaustive list of the grouping criteria: **color**,



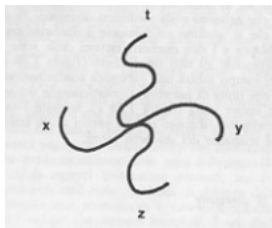
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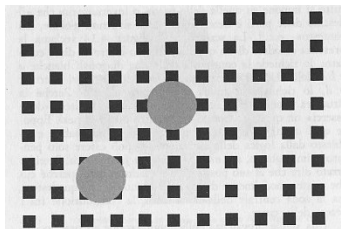
What's a relevant geometric structure?

- ▶ Gestalt theory: underline the importance of perceptual grouping for human visual perception.
- ▶ A non-exhaustive list of the grouping criteria: color, proximity, **good continuation**,



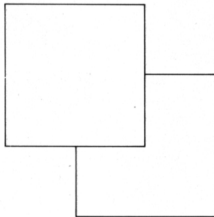
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What's a relevant geometric structure?

- ▶ Gestalt theory: underline the importance of perceptual grouping for human visual perception.
- ▶ A non-exhaustive list of the grouping criteria: color, proximity, good continuation, amodal completion, T-junction, convexity, symmetry, parallelism, closing, perspective, ...

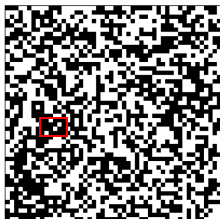
How to detect a relevant geometric structure?

- ▶ Helmholtz principle: relevant geometric structures have a very low probability of occurring in a random context.
- ▶ Example: is the red rectangle relevant?



How to detect a relevant geometric structure?

- ▶ Helmholtz principle: relevant geometric structures have a very low probability of occurring in a random context.
- ▶ Example: is the red rectangle relevant?
 - ▶ Each pixels iid \sim Bernoulli with parameter $p = 0.5$.
 - ▶ Black pixels inside the 6×4 red rectangle R are added.
 - ▶ Let H_0 be the random hypothesis, K a r.v. counting the number of black pixels and \mathcal{B}_{\geq} the binomial tail law:



- $PFA(R) = P_{H_0}(K \geq K(R) = 20 | L(R) = 6 \times 4, p = 0.5) = \mathcal{B}_{\geq}(20, 24, 0.5) \simeq 7.72 \times 10^{-4}$
- $NFA(R) = PFA(R) \times N_{\text{tests}} = 7.72 \times 10^{-4} \times \frac{N(N+1)}{2} \times \frac{M(M+1)}{2} \simeq 1.25 \times 10^3$

How to detect a relevant geometric structure?

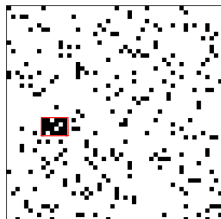
- ▶ Helmholtz principle: relevant geometric structures have a very low probability of occurring in a random context.
- ▶ Example: is the red rectangle relevant?
 - ▶ Each pixels iid \sim Bernoulli with parameter $p = 0.33$.
 - ▶ Black pixels inside the 6×4 red rectangle R are added.
 - ▶ Let H_0 be the random hypothesis, K a r.v. counting the number of black pixels and \mathcal{B}_{\geq} the binomial tail law:



- $PFA(R) = P_{H_0}(K \geq K(R) = 20 | L(R) = 6 \times 4, p = 0.33) = \mathcal{B}_{\geq}(20, 24, 0.33) \simeq 5.53 \times 10^{-7}$
- $NFA(R) = PFA(R) \times N_{\text{tests}} = 5.53 \times 10^{-7} \times \frac{N(N+1)}{2} \times \frac{M(M+1)}{2} \simeq 8.98 \times 10^{-1}$

How to detect a relevant geometric structure?

- ▶ Helmholtz principle: relevant geometric structures have a very low probability of occurring in a random context.
- ▶ Example: is the red rectangle relevant?
 - ▶ Each pixels iid \sim Bernoulli with parameter $p = 0.15$.
 - ▶ Black pixels inside the 6×4 red rectangle R are added.
 - ▶ Let H_0 be the random hypothesis, K a r.v. counting the number of black pixels and \mathcal{B}_{\geq} the binomial tail law:



- $PFA(R) = P_{H_0}(K \geq K(R) = 20 | L(R) = 6 \times 4, p = 0.15) = \mathcal{B}_{\geq}(20, 24, 0.15) \simeq 2.13 \times 10^{-15}$
- $NFA(R) = PFA(R) \times N_{\text{tests}} = 2.13 \times 10^{-15} \times \frac{N(N+1)}{2} \times \frac{M(M+1)}{2} \simeq 3.47 \times 10^{-9}$
- Meaningful test : $NFA(R) < \epsilon$

A generic a contrario detection algorithm

1. Determine a set of N_{tests} candidates $\{x^i\}_{i=1}^{N_{\text{tests}}}$.
2. Estimate, if necessary, statistics on the image (e.g. the Bernouilli parameter p).
3. $\forall i = 1, \dots, N$:
 - ▶ Compute $PFA(x^i)$.
 - ▶ Accept candidate x^i if:

$$NFA(x^i) = N_{\text{tests}} \times PFA(x^i) < \epsilon$$

→ This algorithm produces, on the average, less than ϵ false alarms.

Desolneux edge detection: step one

1. Determine a set of N_{tests} candidates $\{x^i\}_{i=1}^{N_{\text{tests}}}$.

Given a gray level image $u : \Omega \rightarrow \mathbb{R}$, level lines are defined as closed Jordan curves contained in the boundary of a level set with level λ ,

$$\mathcal{X}_\lambda = \{x \in \Omega, u(x) \leq \lambda\} \quad \text{and} \quad \mathcal{X}^\lambda = \{x \in \Omega, u(x) \geq \lambda\},$$

with \mathcal{X}_λ and \mathcal{X}^λ respectively the lower and upper sets, and Ω the image domain.

- No information is lost from the image, which can be reconstructed from the family of lower (or upper) sets.
- Some level set boundaries locally coincide with image contours.
- Candidates are defined using a gray level image.

Desolneux edge detection: step one

1. Determine a set of N_{tests} candidates $\{x^i\}_{i=1}^{N_{\text{tests}}}$.



Somes level lines from the Valbonne church image. For the sake of clarity, only 16 of the 256 levels are illustrated. The Valbonne church image contains 291936 level lines.

Desolneux edge detection: step two

1. Determine a set of N_{tests} candidates $\{x^i\}_{i=1}^{N_{\text{tests}}}$.
2. Estimate, if necessary, statistics on the image.

We define the distribution of the gradient norm of u :

$$\forall \mu > 0, H(\mu) = P(X > \mu) = \frac{\#\{x \in \Omega, |\nabla u(x)| > \mu\}}{\#\{x \in \Omega, |\nabla u(x)| > 0\}}$$

with $|\nabla u(x)|$ the norm of the gradient computed at location x with a 2×2 neighborhood.

Desolneux edge detection: step three

1. Determine a set of N_{tests} candidates $\{x^i\}_{i=1}^{N_{\text{tests}}}$.
2. Estimate, if necessary, statistics on the image.
3. $\forall i = 1, \dots, N$:
 - Compute $PFA(x^i)$ along l_E independent points:

$$PFA(x^i) = H \left(\min_{i=1, \dots, l_E} |\nabla u(x_E^i)| \right)^{l_E}$$

→ $PFA(x^i)$ decreases as l_E and the minimum of gradient along the curve E grow.

- Accept candidate x^i if $NFA(x^i) = N_{\text{tests}} \times PFA(x^i) < \epsilon$

Desolneux edge detection: discussion

Pros:

- ▶ Considered parameter free: the influence of ϵ is logarithmic. In practice, we set $\epsilon = 1$.
- ▶ Suppression of redundant edges using a maximality principle.
- ▶ Fast and efficient.

Cons:

- ▶ Candidates selection.
- ▶ One low level feature.
- ▶ No prior information.

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Introducing edgelets

Terminology:

- ▶ Edgelet: set of M 4-connected pixels

$$w_E^i = (w_E^{i,1}, \dots, w_E^{i,M}) \in \Gamma.$$



- ▶ Edge: set of $k \geq 1$ connected edgelets $E = (w_E^1, \dots, w_E^k)$.

Notations:

- ▶ M is a parameter of the method (in our tests $M = 7$ or $M = 15$).
- ▶ Γ is the set of proper edgelets and is designed such that it excludes self-crossing edgelets.

First feature: prior

1. Learn edgelets of length M using the Berkeley Segmentation DataSet [Fowlkes, Martin, Malik, 2007]:

$M = 7$		$M = 15$	
Edgelets	% of the BDD	Edgelets	% of the BDD
	10.9 %		5.31 %
—	7.89 %	—	2.93 %
↗	1.89 %	↗	0.47 %
↘	1.77 %	↘	0.36 %
↖	1.77 %	↖	0.34 %

Top 5 most representatives edgelets in the BDD.

First feature: prior

1. Learn edgelets of length M using the Berkeley Segmentation DataSet [Fowlkes, Martin, Malik, 2007].
2. Define the likelihood distribution $P(\{y^1, \dots, y^O\}|w)$:

$$\begin{aligned} P_l(w) &= P(\{y^1, \dots, y^O\}|w) \\ &\propto \frac{1}{O} \sum_{i=1}^O [1 + d_F(y^i, w)]^{-1} \end{aligned}$$

with y^o and w two centered edgelets of length M , and d_F the discrete Fréchet distance:

$$d_F(y^o, w) = \inf_{\alpha, \beta} \max_{t \in [0, 1]} d_E[y^o(\alpha(t)), w(\beta(t))]$$

First feature: prior

1. Learn edgelets of length M using the Berkeley Segmentation DataSet [Fowlkes, Martin, Malik, 2007].
2. Define the likelihood distribution $P(\{y^1, \dots, y^O\} | w)$.
3. Estimate offline the AC distribution using a MC procedure:

$$PFA_P(E) = Prior \left(\min_{i=1, \dots, k_E} P_l(w_E^i) \right)^{k_E}$$

with the distribution *Prior* defined by:

$$Prior(\mu) = \frac{1}{U} \# \{z^{(u)}, P_l(z^{(u)}) > \mu\}$$

Second feature: local gradient

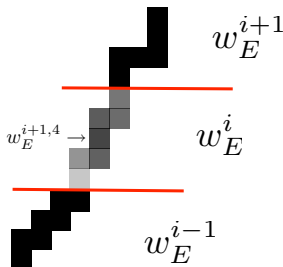
- The *Gradient* distribution is estimated using a online MC procedure. As the prior, the *PFA* is defined such that:

$$PFA_G(E) = Gradient \left(\min_{i=1, \dots, k_E} \left| g(w_E^i) \right| \right)^{k_E}$$

- The local gradient $g(w)$ is computed along a edgelet w :

$$g(w_E^i) = \Phi \left(\left| \nabla u(w_E^{i,1}) \right|, \dots, \left| \nabla u(w_E^{i,M}) \right| \right)$$

- $\Phi = \min$,
- $\Phi = \max$, or
- $\Phi = \sum_{j=1}^M W(j) \times$.



Third feature: textural gradient

- The *Textural* distribution is estimated using a online MC procedure. As the prior, the *PFA* is defined such that:

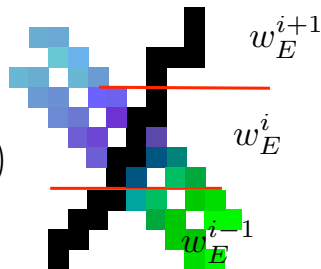
$$PFA_G(E) = \text{Textural} \left(\min_{i=1, \dots, k_E} |t(w_E^i)| \right)^{k_E}$$

- The textural gradient $t(w)$ is computed along a edgelet w :

$$g(w_E^i) = \Psi \left(d_B \left(h[s_1(w_E^{i,1})], h[s_2(w_E^{i,1})] \right), \dots \right.$$

$$\left. d_B \left(h[s_1(w_E^{i,M})], h[s_2(w_E^{i,M})] \right) \right)$$

- $\Psi = \min$,
- $\Psi = \max$, or
- $\Psi = \sum_{j=1}^M W(j) \times$.



Combining several features

Feature fusion:

An edgelet E is said ϵ -meaningful if:

$$NFA(E) = N_E \times \Xi(PFA_1(E), \dots, PFA_F(E)) < \epsilon$$

Fusion operators:

- ▶ $\Xi = \min$: for complementary features (requires to adapt the threshold ϵ).
- ▶ $\Xi = \max$: for competing features.

Valbonne Church [1/2]



(a)



(b)



(c)

Results with $M = 7$ using the (a) prior, (b) local gradient, and (c) textural gradient.

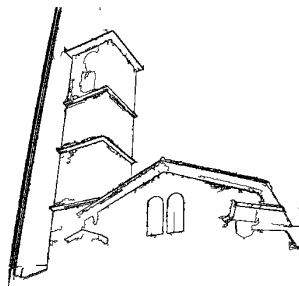
Valbonne Church [2/2]



(a)



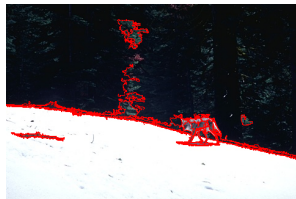
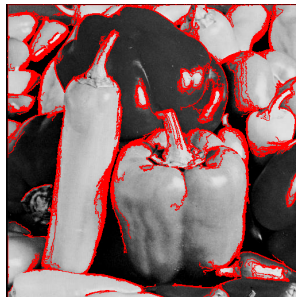
(b)



(c)

Results (a) using the Desolneux model, and our model with (b) $M = 7$ and (c) $M = 15$.

Other results



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Conclusion and perspective

Contributions:

- ▶ Features defined on a higher abstraction level.
- ▶ Prior learned using the BSD.
- ▶ AC distributions estimated using a MC procedure.

Perspective:

- ▶ A contour tracking based on approach to propose candidates during the segmentation process.