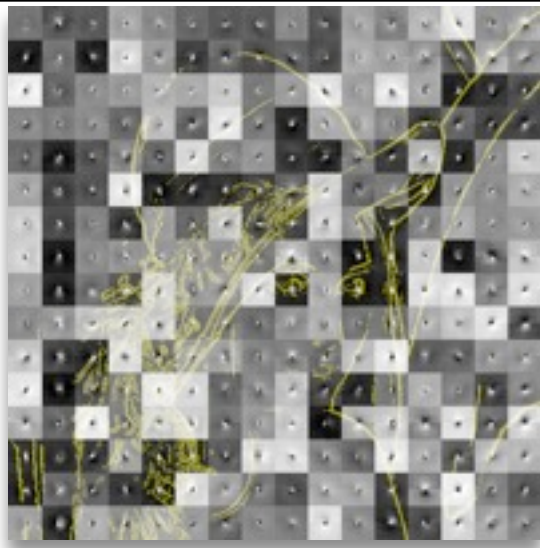


Beyond bits

Reconstructing Images from Local Binary Descriptors



Emmanuel d'Angelo
Alexandre Alahi (Stanford)
Pierre Vandergheynst

Outline

- **Some context**
 - Motivations
 - Local Binary Descriptors
- **LBD reconstruction as an inverse problem**
 - TV-L1, non-binarized case
 - Some examples
- **Ongoing work: L1, binarized reconstruction**
 - A glimpse at our first results
- **Future work and perspectives**

Motivations

- Mobile image recognition services mostly happening «in the cloud»

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Motivations

- **Typical workflow:**
 - Extract features locally, send them over the network
 - «Cloud» matching
 - Send the results back

- **Possible privacy issue**
 - «feature encryption» required ?

- **But there is more:**
 - Smart cameras scenarios
 - Compressed Sensing...

Prior art: inverting SIFT

- Atypical paper, not much related work...
- **One inspiring paper (CVPR'11)**
 - SIFT + **learning database** + Poisson reconstruction



Weinzaepfel, P., Jegou, H., & Pérez, P. (2011). *Reconstructing an image from its local descriptors.*

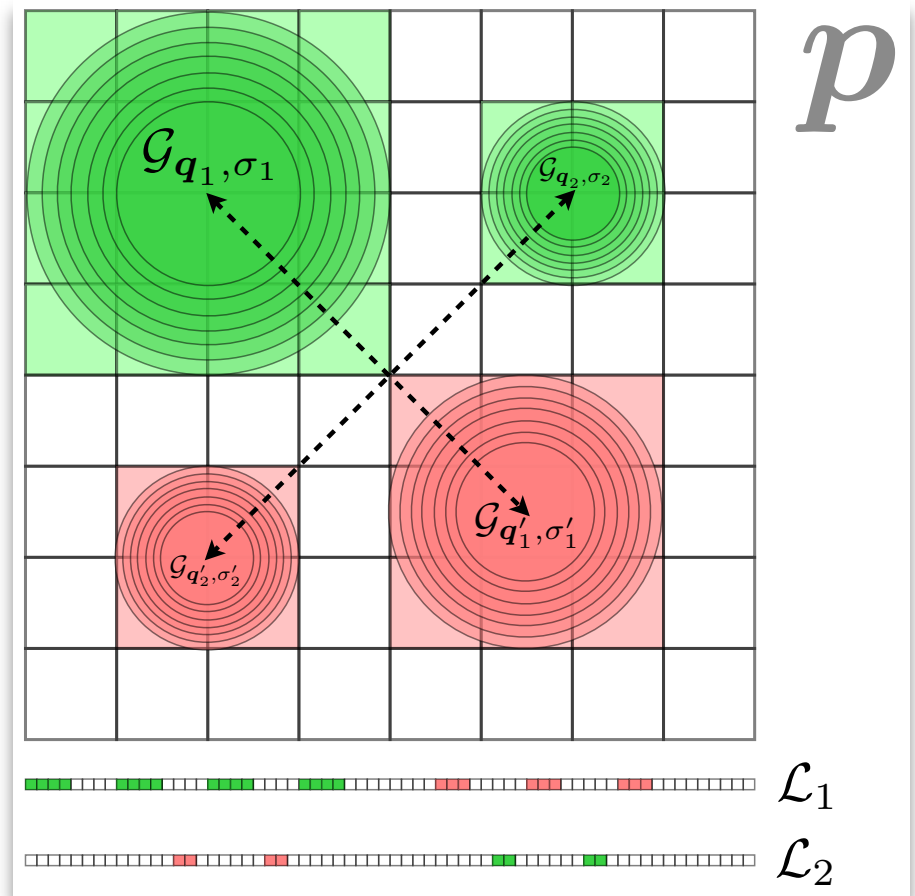
Local Binary Descriptors (LBDs)

1. Differences

$$\mathcal{L}_i = \langle \mathcal{G}_{x_i, \sigma_i}, p \rangle - \langle \mathcal{G}_{x'_i, \sigma'_i}, p \rangle$$

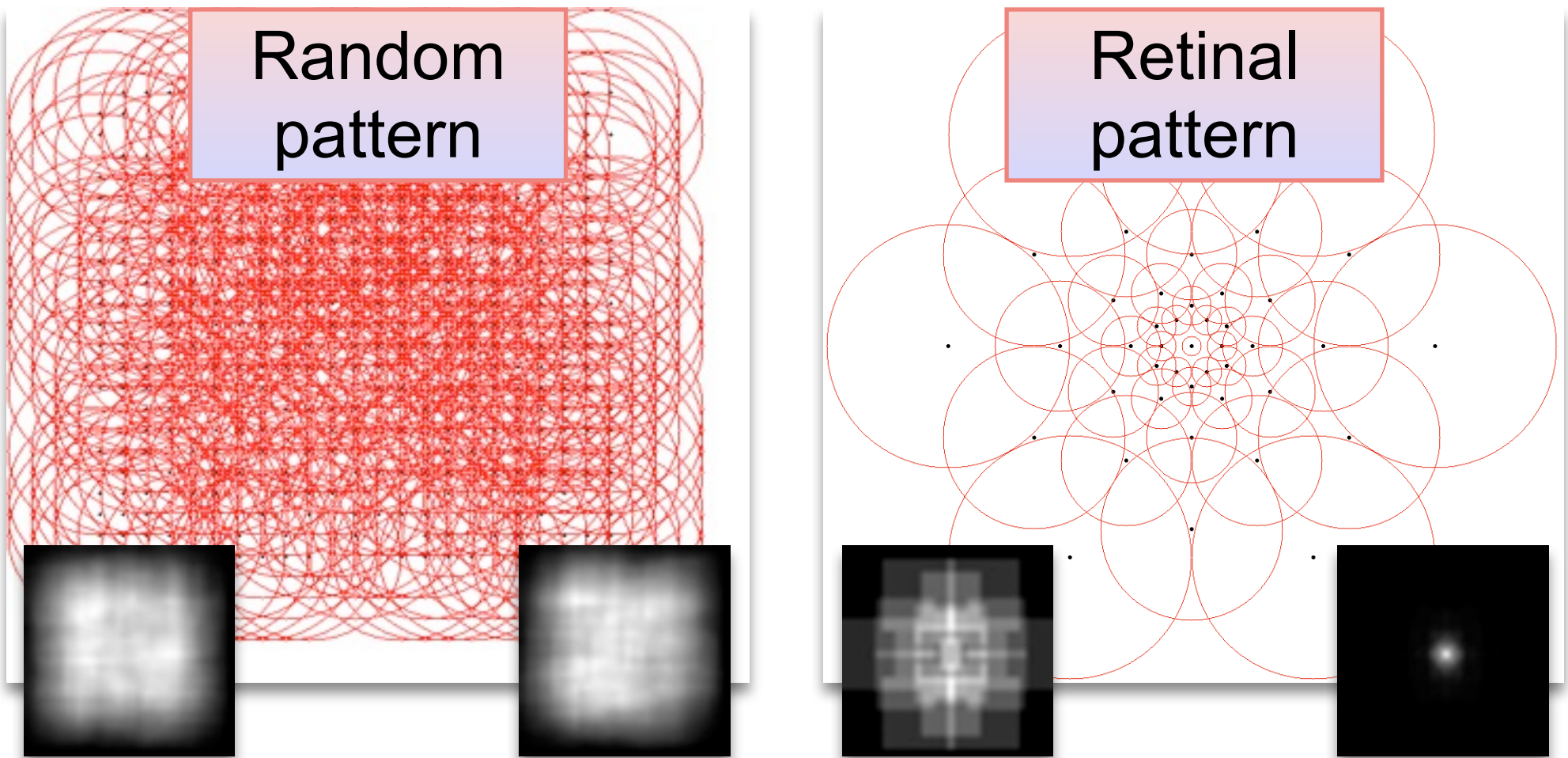
2. Binarization

$$\text{LBD}_i = \mathcal{B}(\mathcal{L}_i)$$



Calonder et al. (2010). *BRIEF: Binary Robust Independent Elementary Features.*

LBDs: BRIEF vs. FREAK



Alahi et al. (2012). *FREAK: Fast Retina Keypoint*.

Variational reconstruction

Better than wavelets!

- What did we measure ? What is our prior ?

$$\hat{p} = \operatorname{argmin}_p \underbrace{\lambda \|A_{\mathcal{L}}p - g\|_1}_{\text{data term}} + \underbrace{\|p\|_{\text{TV}} + \delta_{\mathcal{S}}(p)}_{\text{regularization}}$$

- Fitting the data: robust ℓ_1 -norm of the error
- Prior 1: a patch is piecewise smooth
- Prior 2: mean + dynamic range

Chambolle-Pock primal-dual solver

- Solves a convex functional of the form:

$$\hat{x} = \operatorname{argmin}_x F(Kx) + G(x)$$

- Idea: recast as a saddle point on the **primal** x and the **dual** y :

$$\min_x \max_y \langle Kx, y \rangle_Y + G(x) - F^*(y).$$

- No derivatives involved, but needs the proximal mappings of G and F^*

Chambolle & Pock (2010). *A First-Order Primal-Dual Algorithm for Convex Problems with Applications to Imaging.*

TV-L1 reconstruction algorithm

- Using «cross-and-bouquet» leads to **decoupling** but 2 unknowns (y, z) s.t. $y = A_{\mathcal{L}}p, z = \nabla p$
- **Outline of the iterations:**
 1. Update the **dual** variable of y

$$\text{prox}_{\sigma} F_1^*(q) = \text{sign}(q - \sigma g) \cdot \max(\lambda, |q - \sigma g|)$$
 2. Update the **dual** variable of z

$$(\text{prox}_{\sigma} F_2^*)_i = r_i / \max(1, |r_i|)$$
 3. Update the **primal** unknown by applying the equality and **feasible domain** constraints

A few remarks

- Why is **TV** «better» than **wavelets** ?
 - (+) translation invariant, fast (parallel)
 - (-) flattening effect
- The solver seems complicated...
 - Actually, mostly **pointwise / parallel** operations
- Why the C-P primal-dual and not... ?
 - Mostly a matter of taste and available code !

What about 1-bit LBDs ?

- **Spoiler alert: it works !**
- Ongoing work with A. Alahi, P. Vandergheynst and Laurent Jacques (UC Louvain)
- **Inverse problem with sparsity constraint**
 - No binary prox: Primal-dual (C-P) replaced by **Binary Iterative Hard Thresholding** (Jacques et al.)
 - TV dropped for **wavelet** analysis sparsity (sic)
- **Submitted !** Pre-print available on arXiv.org

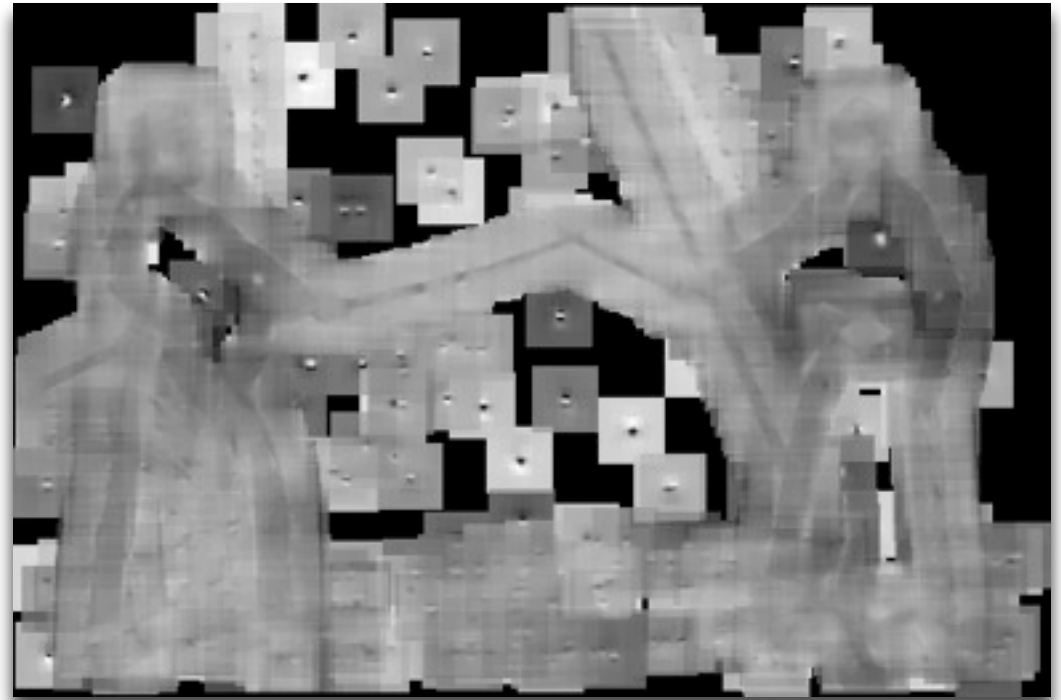
Jacques et al. (2011). *Robust 1-Bit Compressive Sensing via Binary Stable Embeddings of Sparse Vectors.*



1-bit reconstructions results



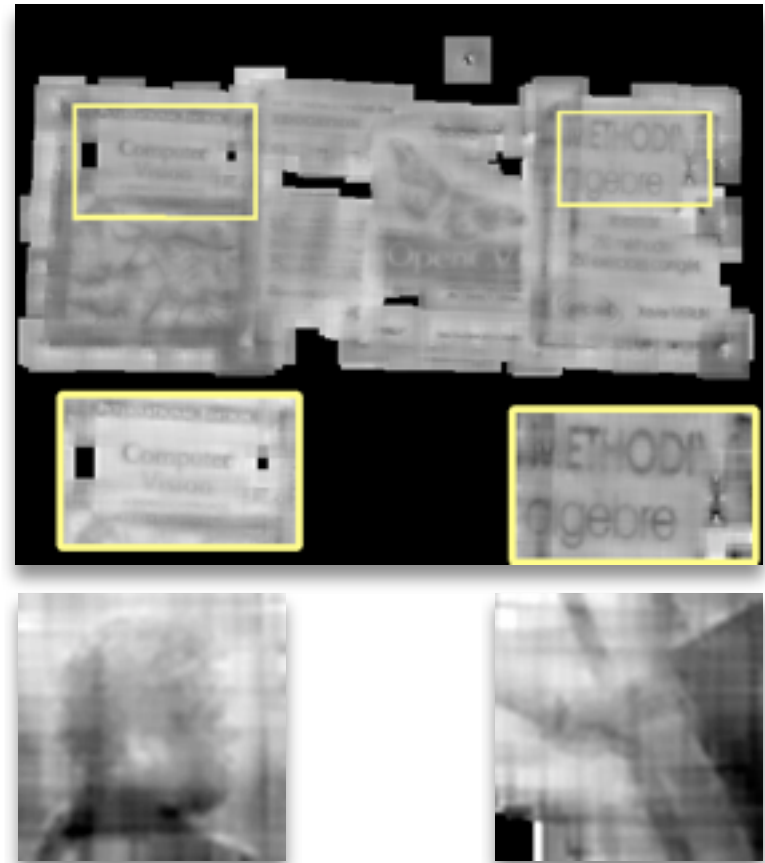
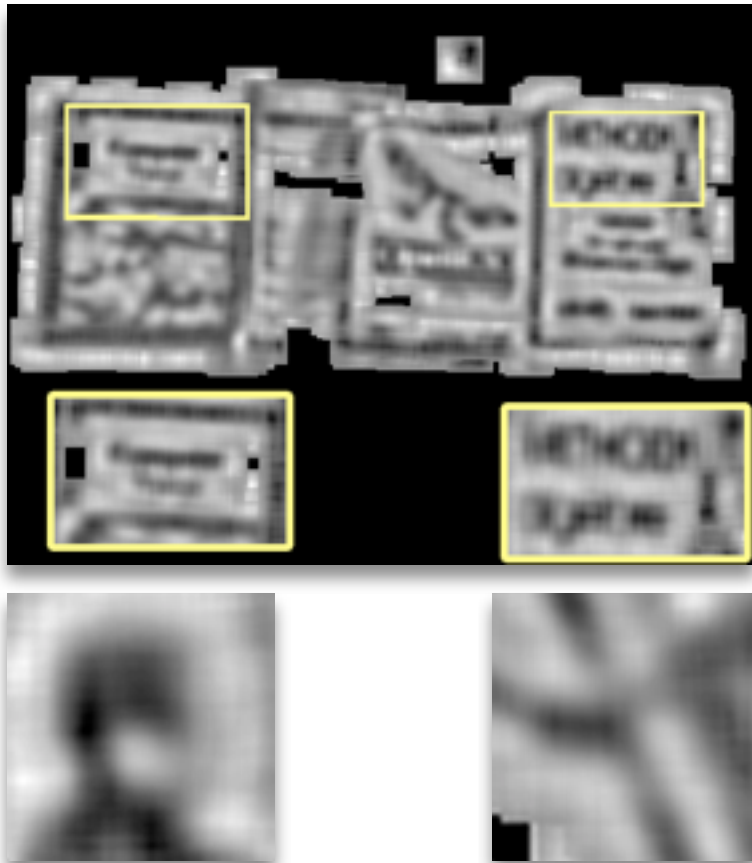
FAST + BRIEF



FAST + FREAK

Bonus: BRIEF vs. FREAK revisited

- They don't encode the same scale !
 - BRIEF captures shapes, FREAK details



Conclusion

- **Wrapping everything up**
 - Reconstruction can be **achieved without learning** even with binarized features
 - The **pattern** has to be known.
 - Shows differences between **LBDs**
- **Privacy matters !**
- **Future work**
 - Hybrid LBD (coarse + fine scale)
 - Better quality using Poisson reconstruction
 - Smart cameras, compression, CS... ?

Thank you !

- **Thank you for your attention**
- Again, thanks to the **reviewers** for their comments about this work
- **1-bit reconstruction links**
 - pre-print: <http://arxiv.org/abs/1211.1265>
 - code: <http://lts2www.epfl.ch/code>

