From Image Restoration to Compressive Sampling in Computational Photography. A Bayesian Perspective.

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Supported by Ministerio de Ciencia e Innovación under contract TIN2010-15137: Bayesian Modeling and Inference in Computational Photography. Design of a prototype of digital camera for multiple exposure and programmable coded aperture.

Outline

- Let’s go back some 25 years (personal experience)
- Image Restoration
- Blind Deconvolution
- Taking pairs of images
- Modifying the aperture
- Capturing the Light Field using Compressive Sensing (CS)
- Our prototype.
- Collaborators

I. Let’s go back some 25 years

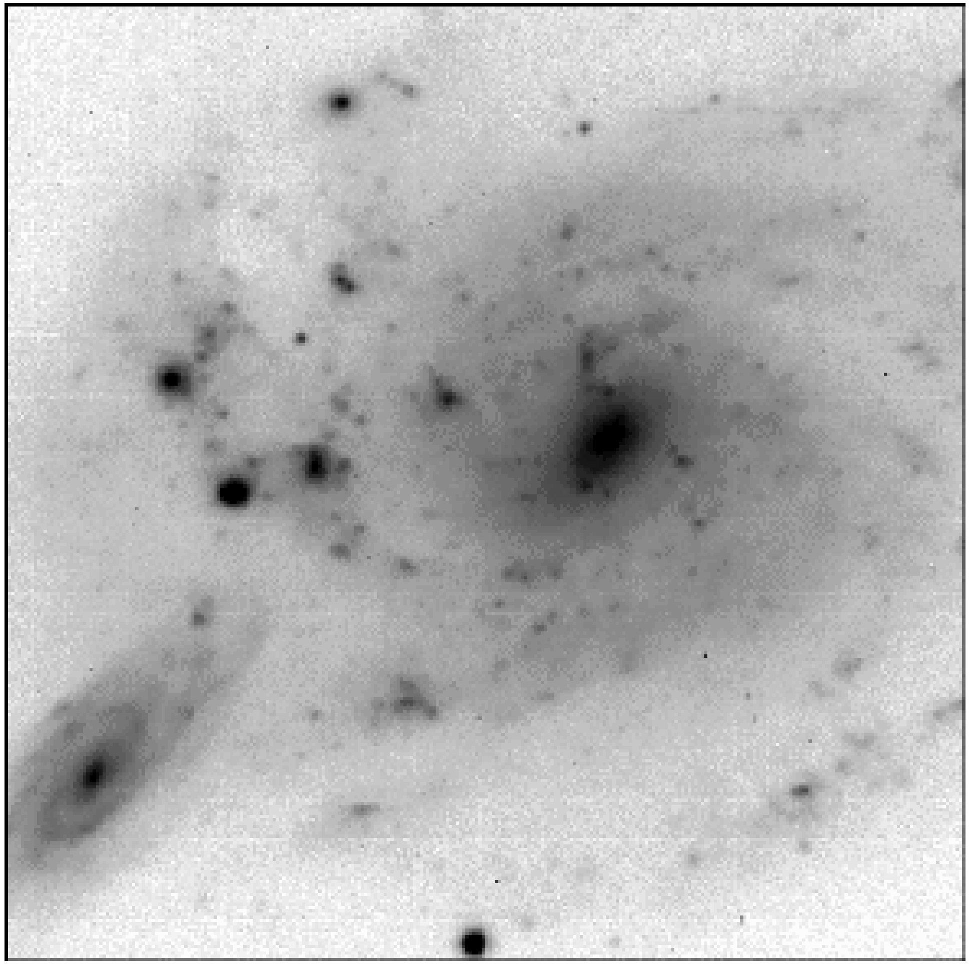


Image provided by the Institute of Astrophysics of Andalucía (IAA) back in 1987

Two galaxies to be deconvolved.

How to do it?

Observation Process $\mathrm{p}(\mathbf{y}|\mathbf{x})$

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \boldsymbol{\epsilon} \qquad \boldsymbol{\epsilon} \sim \mathcal{N}(\underline{0}, \mathrm{diag}(a + b(\mathbf{H}\mathbf{x})_i)$$

we used a robust noise model

Prior knowledge on the image $\mathrm{p}(\mathbf{x})$

de Vaucouleurs' law ($R^{1/4}$-law) for elliptical galaxies

Galaxy dependent parameters

Distance from the center

$$\log(\mathbf{x}(r)/\mathbf{x}_E) = -3.33((r/r_E)^{1/4} - 1)$$

Exponential law for pure disk in a galaxy

$$\mathbf{x}(r) = \mathbf{x}(0)\exp[-b_0 r]$$

We defined

$$\mathbf{z} = \ln(\mathbf{x} + \mathrm{const})$$

and used a conditional or simultaneous auto-regression (CAR o SAR) as prior on **z**

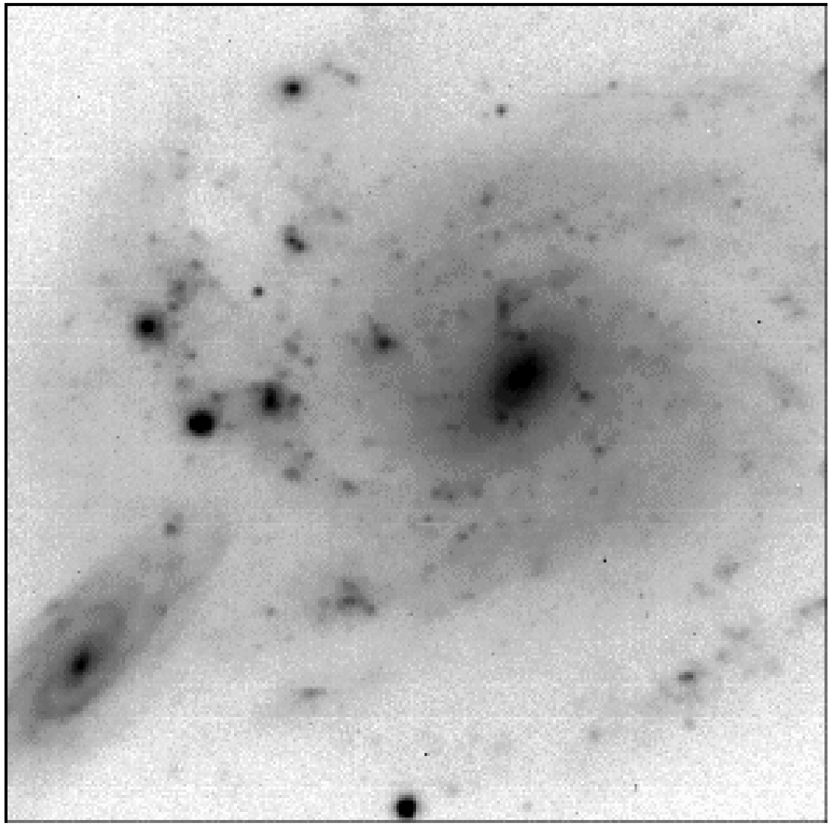
Inference

$$\hat{\mathbf{z}} = \arg\max_{\mathbf{z}} p(\mathbf{z}|\mathbf{y}) = \arg\max_{\mathbf{z}} \mathrm{p}(\mathbf{z})\mathrm{p}(\mathbf{y}|\mathbf{z})$$

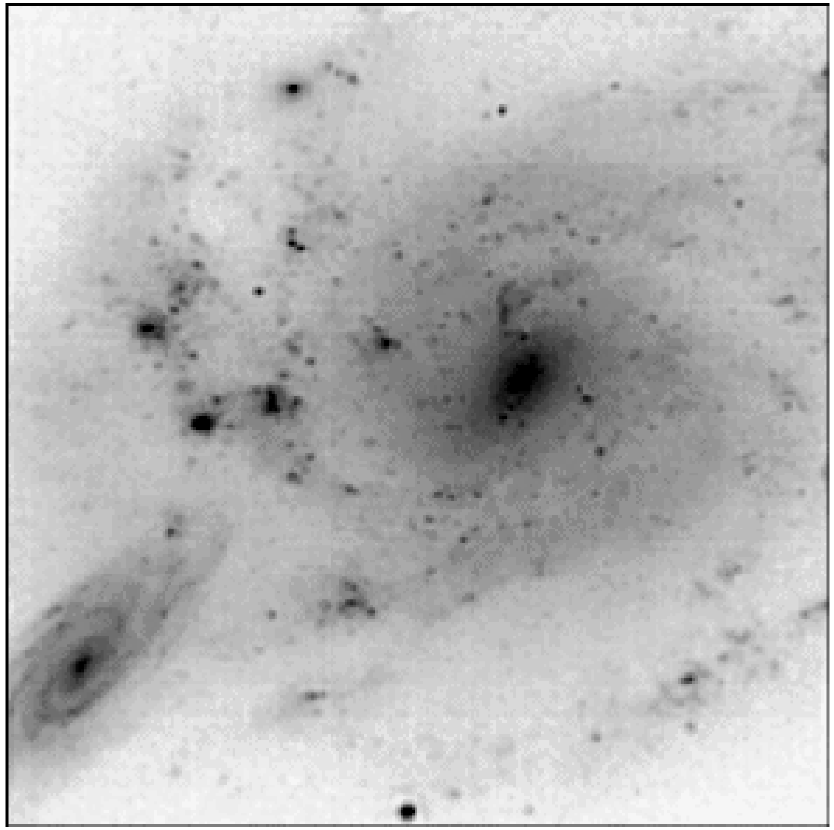
R. Molina, and B.D. Ripley, "Using Spatial Models as Priors in Astronomical Image Analysis", Journal of Applied Statistics, vol. 16, 193-206, 1989.

R. Molina, A. del Olmo, J. Perea, and B.D. Ripley, "Bayesian Deconvolution in Optical Astronomy", The Astronomical Journal, vol. 103, 666-675, 1992.

R. Molina, "On the Hierarchical Bayesian Approach to Image Restoration. Applications to Astronomical Images", IEEE PAMI. vol. 16, 1122-1128, 1994.



observation



restoration

II. Image Restoration (in its simplest form)

Observation Process $\mathrm{p}(\mathbf{y}|\mathbf{x})$

Known

Unknown

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \boldsymbol{\epsilon}$$

Prior knowledge on the image $\mathrm{p}(\mathbf{x})$

Initially:

Flat priors (Richardson-Lucy method)

quadratic energy functions (CAR or SAR image priors)

inclusion of line process (Work by Geman and Geman on SA)

quadratic regularization in the signal/image processing community

Inference

Try to know as much as possible of $\mathrm{p}(\mathbf{x}|\mathbf{y})$

Initially only the Maximum A Posteriori (MAP)

R. Molina, A.K. Katsaggelos, and J. Mateos, “Bayesian and Regularization Methods for Hyperparameter Estimation in Image Restoration”, IEEE TIP, vol. 8, 231-246, 1999

II. Image Restoration (in its simplest form)

Bayesian Modeling

$$\mathrm{p}(\boldsymbol{\Theta}, \mathbf{x}, \mathbf{y}) = \mathrm{p}(\boldsymbol{\Theta})\mathrm{p}(\mathbf{x}|\boldsymbol{\Theta})\mathrm{p}(\mathbf{y}|\mathbf{x}, \boldsymbol{\Theta})$$

Bayesian Inference

Calculate, approximate or simulate

$$\mathrm{p}(\boldsymbol{\Theta}, \mathbf{x}|\mathbf{y}) = \frac{\mathrm{p}(\boldsymbol{\Theta}, \mathbf{x}, \mathbf{y})}{\mathrm{p}(\mathbf{y})}$$

It is very far away from calculating

$$\hat{\mathbf{x}}(\boldsymbol{\Theta}) = \arg\max_{\mathbf{x}} \mathrm{p}(\boldsymbol{\Theta}, \mathbf{x}, \mathbf{y})$$

II. Image Restoration (in its simplest form)

On Richardson-Lucy Method

$$\mathrm{p}(\mathbf{y}|\mathbf{x}) = \prod_i \exp[-(\mathbf{Hx})_i]\frac{(\mathbf{Hx})^{y_i}}{y_i!}$$

Differentiating -ln(p(**y**|**x**)) with respect to **x**

$$\mathbf{1} = \mathbf{H}^t\left(\frac{\mathbf{y}}{\mathbf{Hx}}\right) \Longrightarrow \mathbf{x}^{\mathrm{k}+1} = \mathbf{x}^{\mathrm{k}}.*\,\mathbf{H}^{\mathrm{t}}\left(\frac{\mathbf{y}}{\mathbf{Hx}^{\mathrm{k}}}\right)$$

Shares the same problems as utilizing for Gaussian noise

$$\mathbf{x}^{\mathrm{k}+1} = \mathbf{x}^{\mathrm{k}}.*\left(\frac{\mathbf{H}^{\mathrm{t}}\mathbf{y}}{\mathbf{H}^{\mathrm{t}}\mathbf{Hx}^{\mathrm{k}}}\right)$$

II. Image Restoration

(Some) interesting image prior models

TV- prior (first sparse prior?)

$$\mathrm{p}(\mathbf{x}|\alpha) \propto \frac{1}{Z_{\mathrm{TV}}(\alpha)} \exp\left[-\alpha \mathrm{TV}(\mathbf{x})\right]$$

L. I. Rudin, S. Osher, and E. Fatemi, "Nonlinear total variation based noise removal algorithms," Physica D, 259–268, 1992.

Sparse priors

$$\mathbf{x} = \mathbf{A}\mathbf{w} \qquad \ln \mathrm{p}(\mathbf{w}|\lambda) = -\lambda\rho(\mathbf{w}) + \mathrm{const}$$

dictionary sparse

Based on l1-norm or lp-(quasi)norms p<1

M. Elad, *Sparse and Redundant Representations: From Theory to Applications in Signal and Image Processing*,Springer, 2010

J.-L. Starck, F. Murtagh, J.M. Fadili, *Sparse Image and Signal Processing : Wavelets, Curvelets, Morphological Diversity*, Cambridge, 2010

II. Image Restoration

<u>Variational inference</u> (see also MCMC and Belief Propagation)

$$\begin{aligned}\hat{\mathrm{q}}(x) &= \arg\min_{\mathrm{q}(\mathbf{x})} \int \mathrm{q}(\mathbf{x}) \log\left(\frac{\mathrm{q}(\mathbf{x})}{\mathrm{p}(\mathbf{x}|\mathbf{y})}\right) d\mathbf{x} \\ &= \arg\min_{\mathrm{q}(\mathbf{x})} \int \mathrm{q}(\mathbf{x}) \log\left(\frac{\mathrm{q}(\mathbf{x})}{\mathrm{p}(\mathbf{x},\mathbf{y})}\right) d\mathbf{x} + \mathrm{const}\end{aligned}$$

Some constraints may apply.
No parameters included for simplicity

M. I. Jordan, Z. Ghahramani, T. S. Jaakola, and L. K. Saul, "An Introduction to variational methods for graphical models," in *Learning Graphical Models. Cambridge, MA: MIT Press, 1998, pp. 105–162.*

J. Miskin, "Ensemble learning for independent component analysis," Ph.D. dissertation, Astrophysics Group, Univ. Cambridge, Cambridge, U.K., 2000.

M. J. Beal, "Variational algorithms for approximate bayesian inference," Ph.D. dissertation, The Gatsby Computational Neuroscience Unit, Univ. College London, London, U.K., 2003.

II. Image Restoration

An important inequality

$$u^{p/2} v^{1-p/2} \leq \frac{p}{2} u + (1 - \frac{p}{2}) v \qquad u \geq 0, v > 0, 0 < p \leq 2$$

$$u^{p/2} \;\leq\; \frac{p}{2} \frac{u + \frac{2-p}{p} v}{v^{1-p/2}}$$

so

$$u^{p} \;\leq\; \frac{p}{2} \frac{u^2 + \frac{2-p}{p} v}{v^{1-p/2}}$$

This bound leads to the majorization of sparse energies using Gaussian distributions

J. Bioucas-Dias, M. Figueiredo, and J. Oliveira, “Adaptive Bayesian total-variation image deconvolution: A majorization minimization approach,” EUSIPCO 2006.
J.A. Palmer, D.P. Wipf, K. Kreutz-Delgado, and B.D. Rao, ``Variational EM Algorithms for Non-Gaussian Latent Variable Models," NIPS, 2006

II. Image Restoration

Majorization for TV

$$\mathrm{TV}(\mathbf{x}) \leq \sum_i \frac{(\Delta_i^h(\mathbf{x}))^2 + (\Delta_i^v(\mathbf{x}))^2 + u_i}{\sqrt{u_i}}$$

S.D. Babacan, R. Molina, and A.K. Katsaggelos, “Parameter Estimation in TV Image Restoration Using Variational Distribution Approximation”, IEEE TIP, vol. 17, 326-339, 2008.

Majorization for Fields of Experts

Combine pairs the output of couples of filters (j) with energies

$$\sum_i \sqrt{(\epsilon^{2j}(i))^2 + (\epsilon^{2j+1}(i))^2}$$

G. Chantas, N. Galatsanos, R. Molina, and A.K. Katsaggelos, “Variational Bayesian Image Restoration with a Spatially Adaptive Product of Total Variation Image Priors, IEEE TIP, vol. 19, 351-362, 2010.

III. Blind Deconvolution

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \boldsymbol{\epsilon}$$

unknowns

See next talk

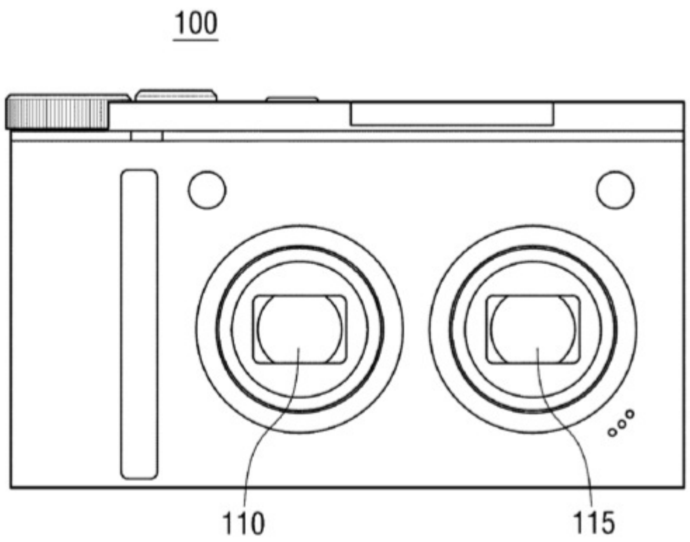
Yair Weiss “Old and New algorithm for Blind Deconvolution”

A. C. Likas and N. P. Galatsanos, “A variational approach for Bayesian blind image deconvolution,” *IEEE Trans. Signal Process., vol. 52, no.* 8, pp. 2222–2233, Aug. 2004.

IV. Taking pairs of images

There are many IP/CV problems where using two images can greatly helps.

SynthCam: Shallow Depth-of-Field Photos on iPhone by M. Levoy (image + video)



Samsung camera patent to blur background

IV. Taking pairs of images

Blurred/noisy pair combination

Long Exposure

Short Exposure

L. Yuan, J. Sun, L. Quan, and H.-Y. Shum, “Image deblurring with blurred/noisy image pairs,” in *Proc. SIGGRAPH Conf., New York,* 2007, p. 1.

IV. Taking pairs of images

Blurred/noisy pair combination

Long Exposure Image, t =1/3 s, ISO 800

Short Exposure Image, t= 1/100 s, ISO 800

IV. Taking pairs of images

Long Exposure Image

Camera Shake Blur

$$\mathbf{y}_1 = \mathbf{H}\mathbf{x} + \mathbf{n}_1$$

Short Exposure Image

Geometric Registration

$$\lambda_1 \mathbf{C}\mathbf{y}_2 + \lambda_2 \mathbf{1} = \mathbf{x} + \mathbf{n}_2$$

Photometric Registration

Preprocessing

$$\mathbf{y}_2 = \mathbf{x} + \mathbf{n}_2$$

Information on **H**, negligible?

$$\mathbf{y}_1 = \mathbf{H}\mathbf{y}_2 + \mathbf{n}_3$$

IV. Taking pairs of images

$$\mathbf{y}_1 = \mathbf{H}\mathbf{y}_2 + \mathbf{n}_3$$

This observation model, which has only information on the blur, comes from ideas in

F. Sroubek and J. Flusser, "Multichannel blind deconvolution of spatially misaligned images," *IEEE Trans. Image Process., vol. 14, no. 7,* 874–883,2005.

It has been used in the dual exposure problem

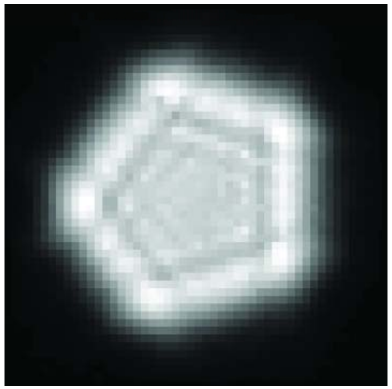
D. Bababan, R. Molina, and A.K. Katsaggelos, "Bayesian Blind Deconvolution from Differently Exposed Image Pairs", IEEE TIP, vol. 19, 2874-2888, 2010.

V. Modifying the aperture

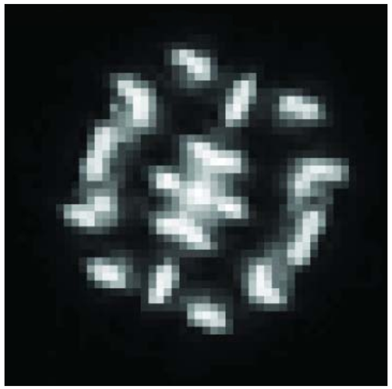
(Some) interesting models

Can we modify the aperture for better depth discrimination?

Aperture patterns



Psf

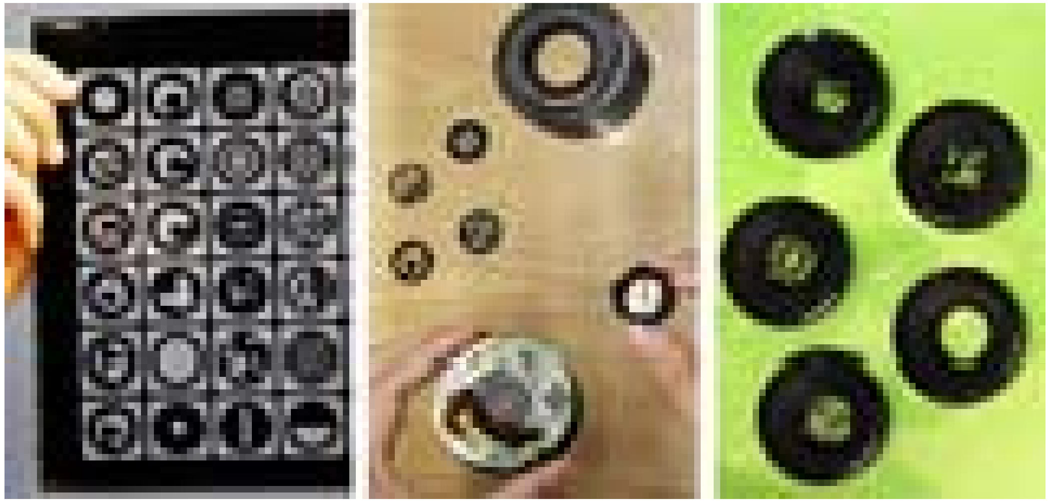


The pattern is selected based on maximizing the KL divergence of the marginal distributions of the observations at different blur scales. CAR or SAR prior image models are assumed.

A. Levin, R. Fergus, F. Durand, W. T. Freeman, “Image and Depth from a Conventional Camera with a Coded Aperture”. SIGGRAPH, ACM Transactions on Graphics, Aug 2007.

V. Modifying the aperture

Evaluating aperture patterns based on the quality of the deblurred image



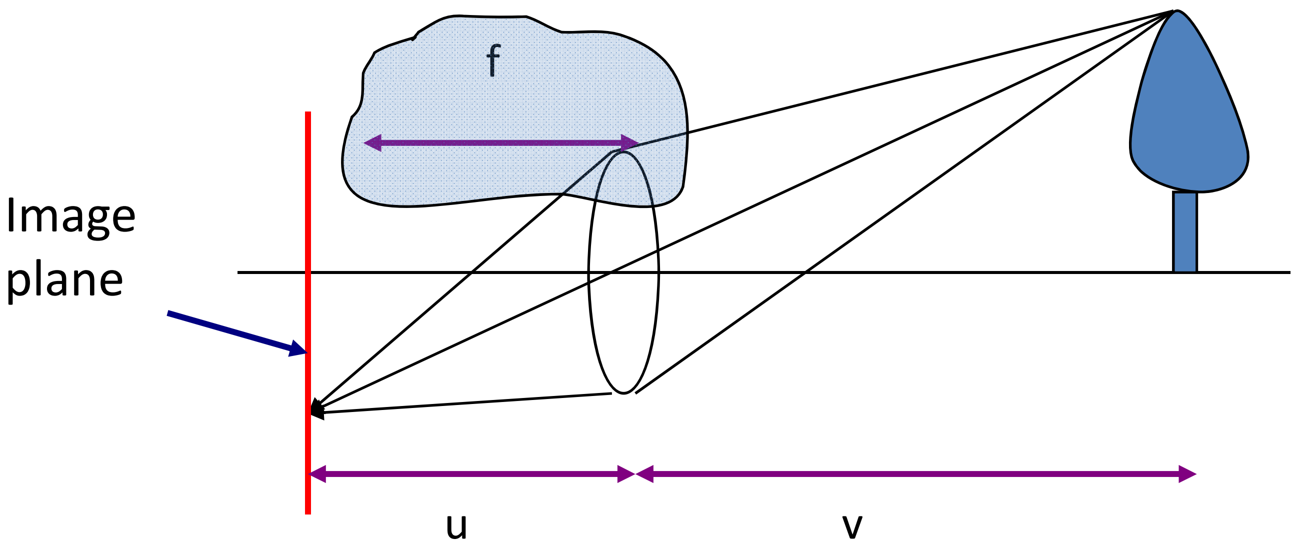
The expected value of the L2-norm between the restoration and the original image is minimized.

C. Zhou and S. K. Nayar, "What are Good Apertures for Defocus Deblurring?," IEEE International Conference on Computational Photography, Apr, 2009.

For pairs of aperture pattern see, for instance,

C. Zhou and S. K. Nayar, and S. Lin, Coded Aperture Pairs for Depth from Defocus and Defocus Deblurring, International Journal of Computer Vision , vol. 93, 1, 2011.

VI. Capturing the Light Field using CS

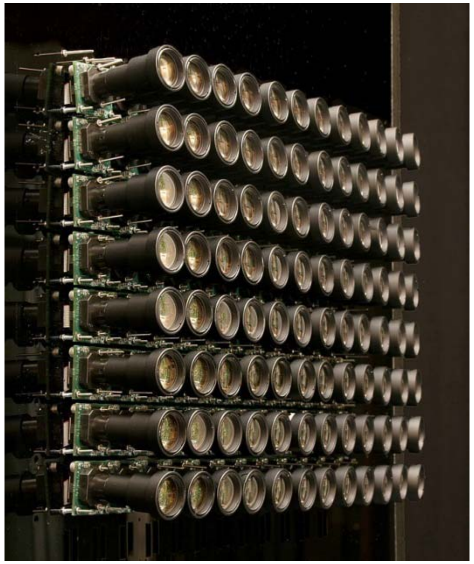


Thin Lens equation

$$1/u + 1/v = 1/f$$

VI. Capturing the Light Field using CS

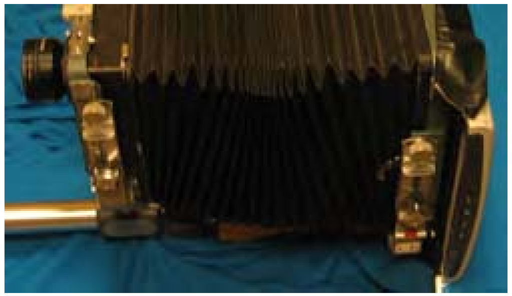
Wilburn *et. al. 2005*



Ng *et. al. 2005*

Georgiev *et. al. 2006*

Veeraraghavan *et. al. 2007*



VI. Capturing the Light Field using CS

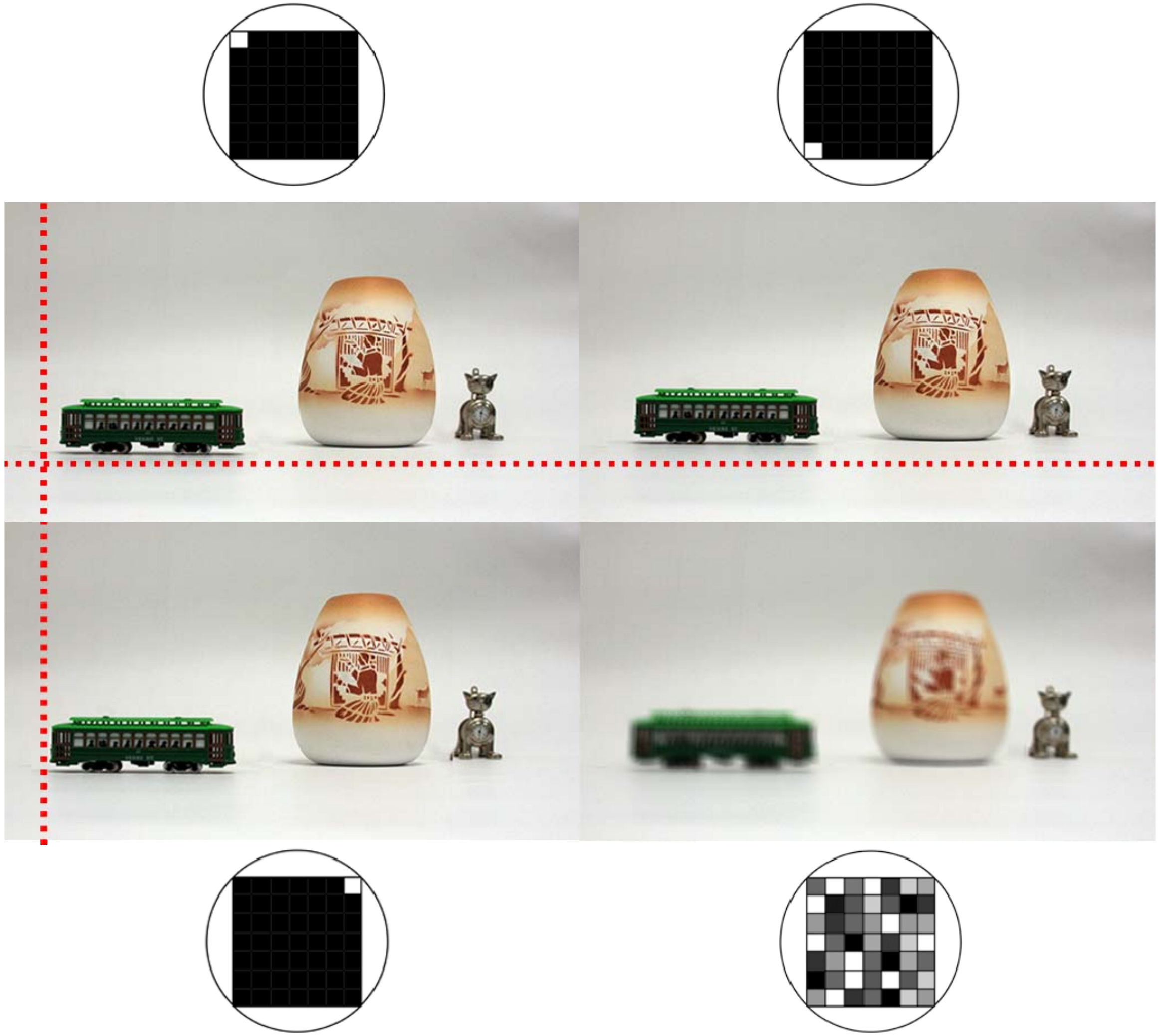
Liang *et. al. 2008*

C.-K. Liang, T.-H. Lin, B.-Y. Wong, C. Liu, and H. H. Chen, "Programmable aperture photography: multiplexed light field acquisition," *ACM Trans. Graph., pp. 1–10, 2008.*

S. D. Babacan, R. Ansorge, M. Luessi, R. Molina, and A.K. Katsaggelos, "Compressive Sensing of Light Fields" in *IEEE International Conference on Image Processing (2009)*, 2337-2340, 2009.

A. Ashok and M.A. Neifeld, "Compressive Light Field Imaging," Proc. of SPIE 7690, 3D Visualization and Processing II, 76900Q, 2010.

VI. Capturing the Light Field using CS



VI. Capturing the Light Field using CS

Compressive coding of the aperture

$$
\begin{pmatrix} \mathbf{y}^1 \\ \mathbf{y}^2 \\ \cdot \\ \cdot \\ \mathbf{y}^M \end{pmatrix} = \begin{pmatrix} a^{11}\mathbf{I} & a^{12}\mathbf{I} & \cdot & \cdot & a^{1N}\mathbf{I} \\ a^{21}\mathbf{I} & a^{22}\mathbf{I} & \cdot & \cdot & a^{2N}\mathbf{I} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ a^{M1}\mathbf{I} & a^{M2}\mathbf{I} & \cdot & \cdot & a^{MN}\mathbf{I} \end{pmatrix} \begin{pmatrix} \mathbf{x}^1 \\ \mathbf{x}^2 \\ \cdot \\ \cdot \\ \mathbf{x}^N \end{pmatrix}
$$

M observations Random measurement matrix N angular images

$$
\boxed{\mathbf{y} = \mathbf{A}\mathbf{x}}
$$

and apply Compressive Sensing theory. See the paper

S. D. Babacan, R. Ansorge, M. Luessi, R. Molina, and A.K. Katsaggelos, "Compressive Sensing of Light Fields" in *IEEE International Conference on Image Processing* 2337-2340, 2009.

VI. Capturing the Light Field using CS

- Scrambled Hadamard (binary) or uniform ensembles (grey-valued)

- Collect more light than single openings
- Nonlinear reconstruction

➡ High signal to noise ratio

➡ High spatial and angular resolution

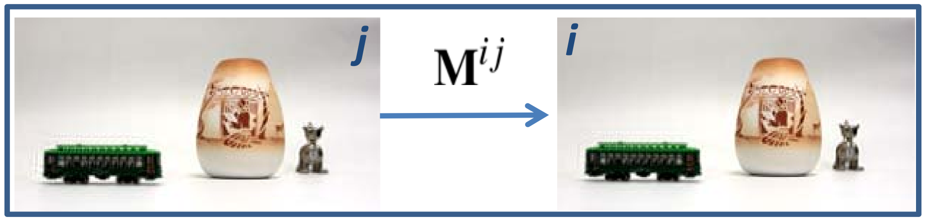
VI. Capturing the Light Field using CS

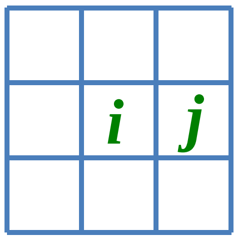
Reconstruction of Light Field

– Intra-image priors

$$p(\mathbf{x}|\boldsymbol{\alpha}_{\mathrm{TV}}) \propto \prod_{i=1}^{N} \left(\alpha_{\mathrm{TV}}^{i}\right)^{P/2} \exp\left[-\frac{1}{2}\alpha_{\mathrm{TV}}^{i}\,\mathrm{TV}(\mathbf{x}^{i})\right]$$

– Inter-image priors

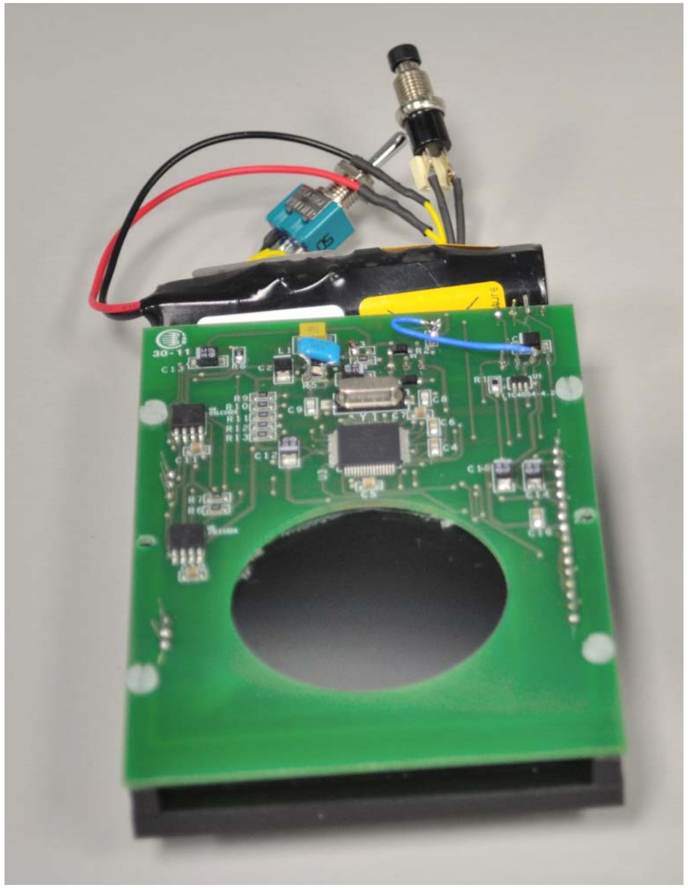




$$p(\mathbf{x}|\boldsymbol{\alpha}_{c}) \propto \exp\left(\sum_{i=1}^{N}\sum_{j\in\mathcal{N}(i)} -\frac{\alpha_{c}^{ij}}{2} \| \mathbf{x}^{i} - \mathbf{M}^{ij}\mathbf{x}^{j} \|_{\mathbf{O}^{ij}}^{2}\right)$$

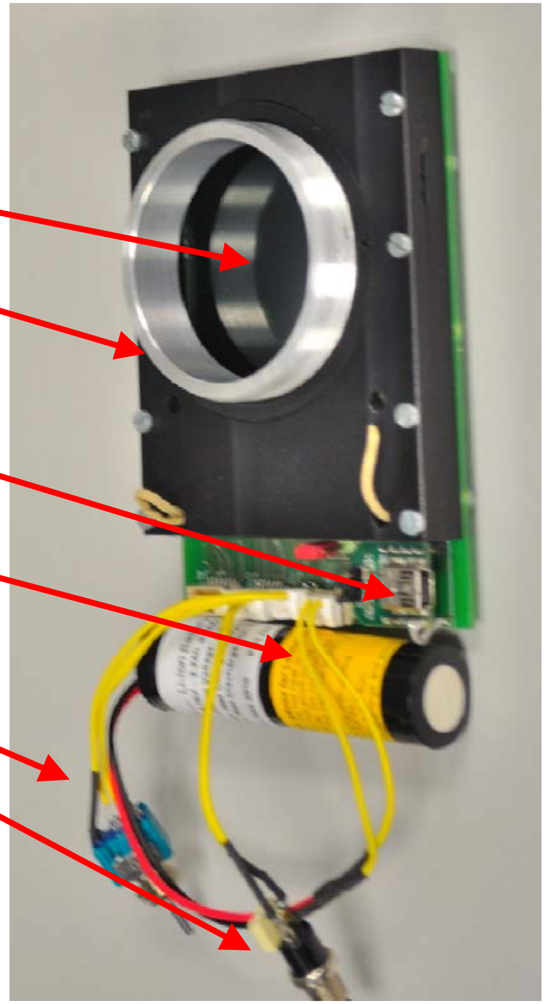
VII. Our prototype

- Prototype developed at the Institute of Astrophysics of Andalucía
- LCD of 160x104 pixels.
- Only 104x104 are used.
- LCD size: 78x61x2.8mm.
- 4 gray levels per pixel.



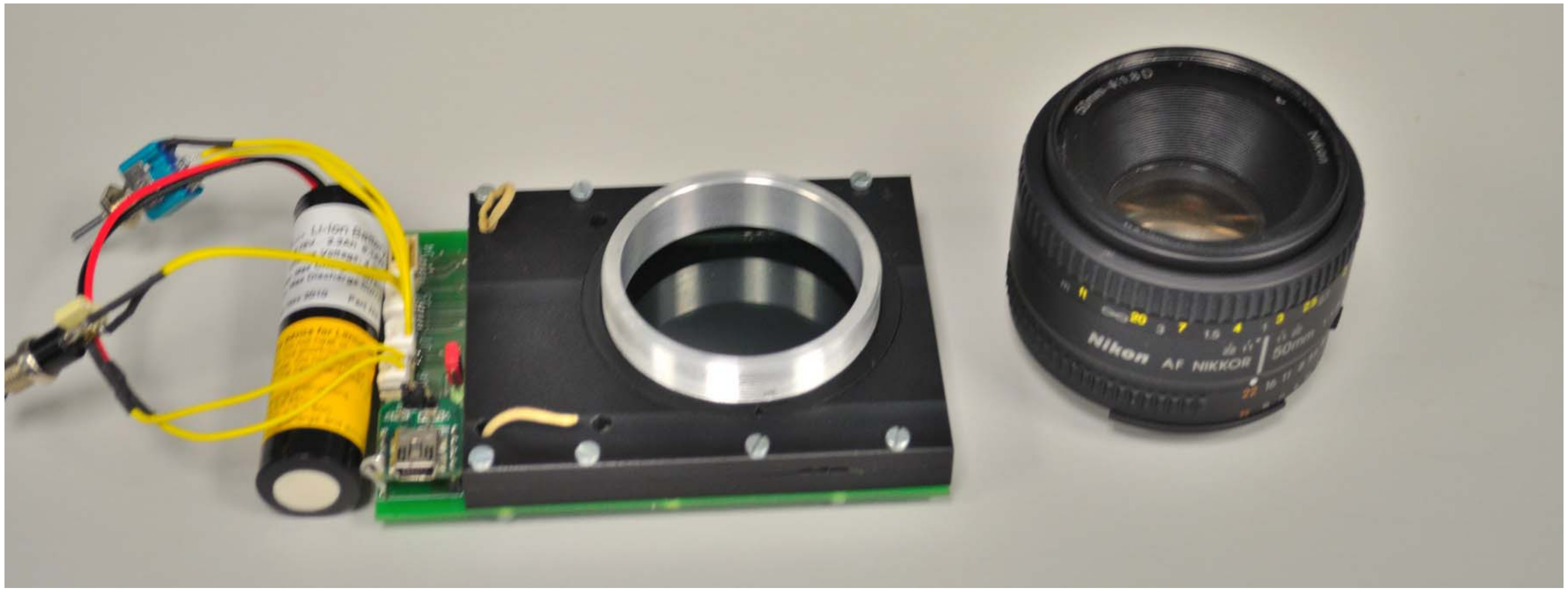
VII. Our prototype

- LCD panel
- To attach to the lens
- USB connection
- Battery Pack
- Power switch
- Mask change switch
- Memory for 160 binary masks or 80 masks with 4 gray levels.



VII. Our prototype

- It can be mounted as a filter on any 52mm diameter lens.
- We used a Nikon Nikkor AF 50mm f/1.8 D.



VII. Our prototype

Mounted on the lens.

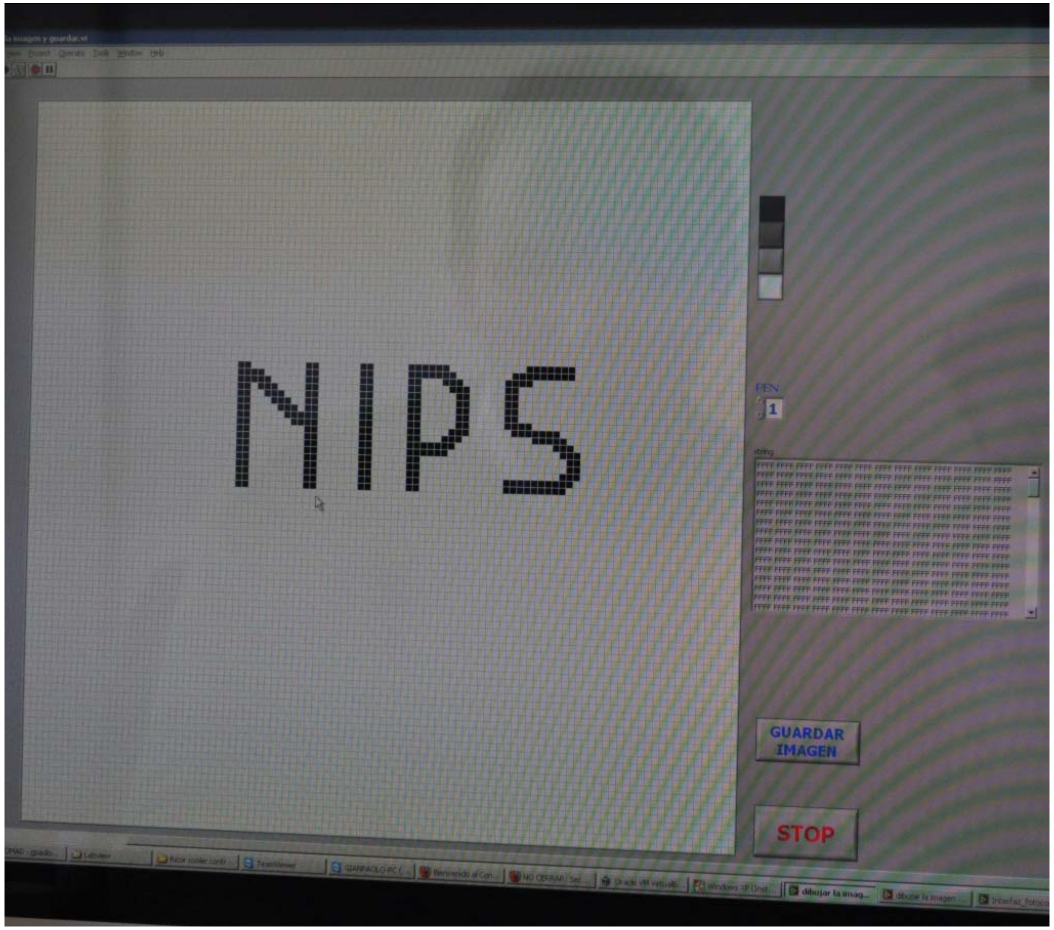
Light weight.

Pictures can comfortably be taken with the prototype attached to the lens

VII. Our prototype

Mask editor (still being developed)

- 4 gray levels.
- 104x104 masks.
- allows to create a mask from an image.
- allows to transfer the masks from and to the prototype.



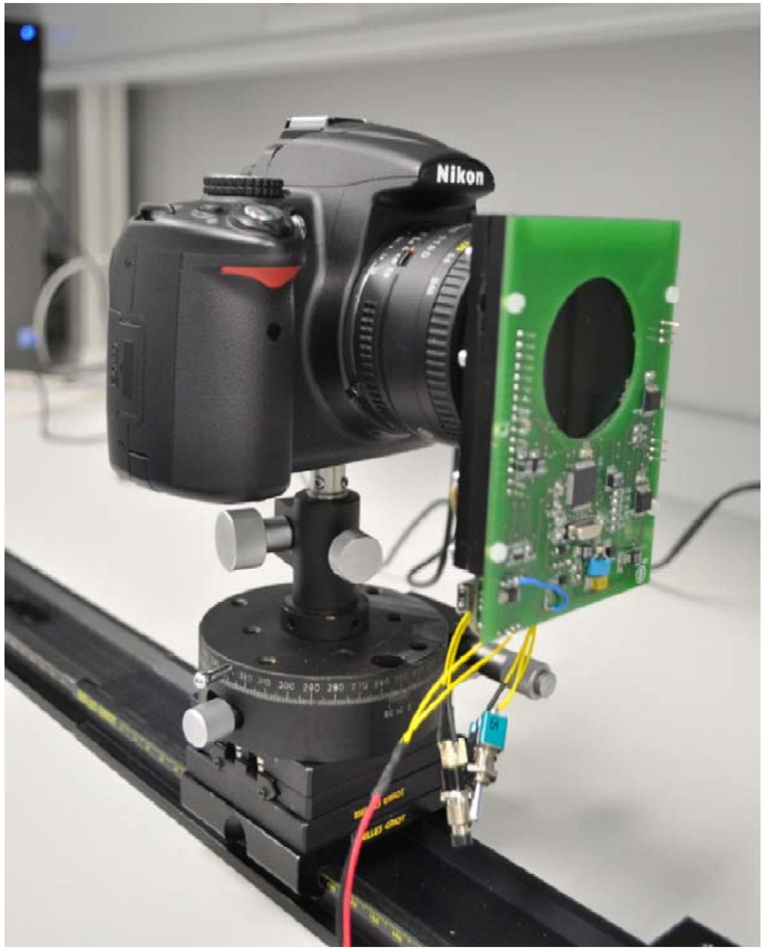
VII. Our prototype

LCD displaying the transferred mask.

A connection to the computer is only needed for transferring the masks.

VII. Our prototype

- The setup:
- Nikon D5000
- 12.3 Mpixel
- DX sensor, CMOS, 23.6 x 15.8 mm.
- Lens: Nikon Nikkor AF 50mm f/1.8 D



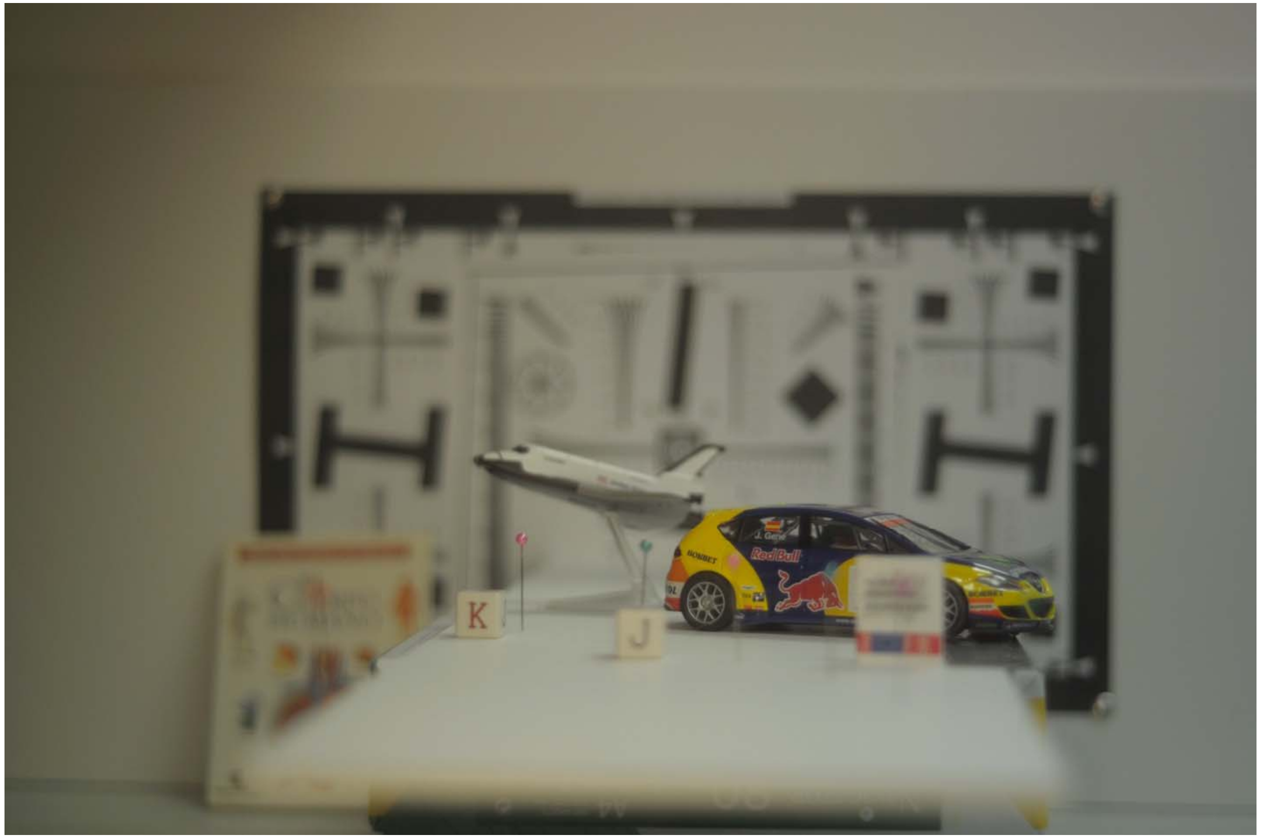
VII. Our prototype

- No LCD

f/1.8, 1/320 s.

VII. Our prototype

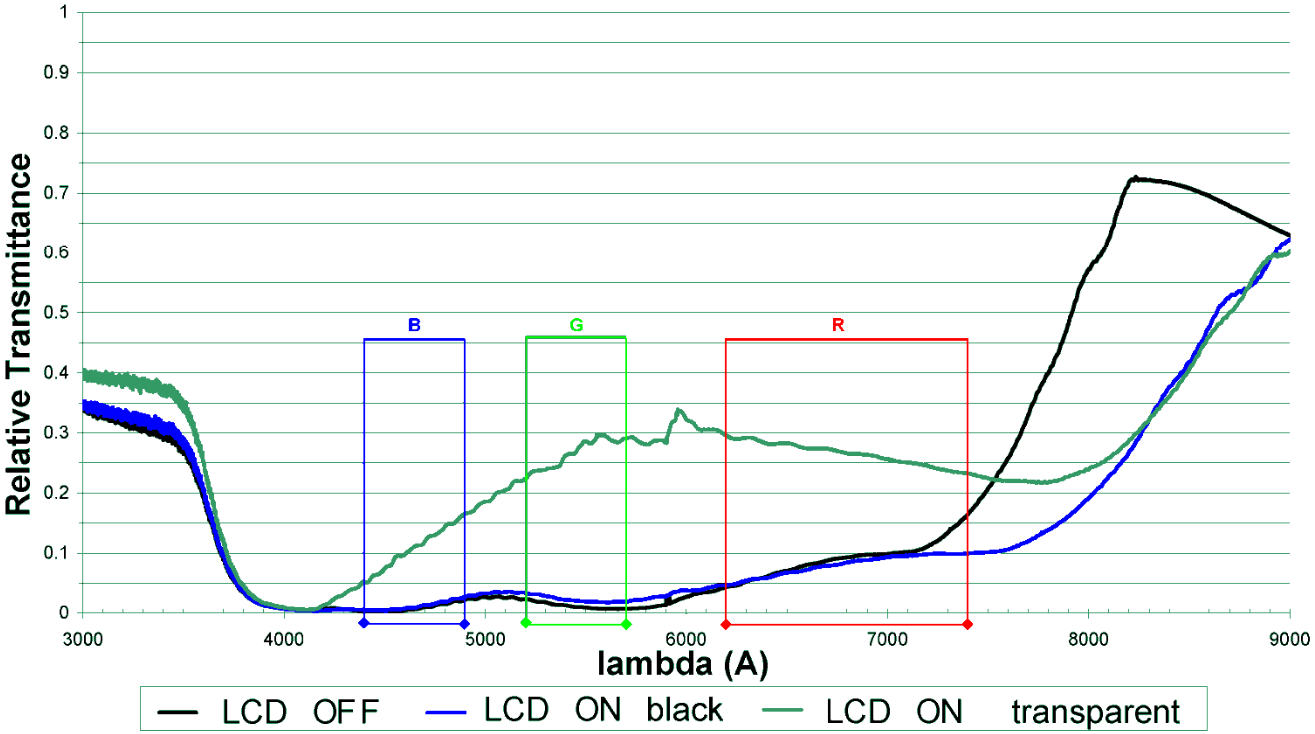
- Transparent LCD. Automatic white balance



f/1.8, 1/100 s.

VII. Our prototype

- LCD transmittance



No LCD. 1/320s

LCD transparent. 1/100s

VII. Our prototype

- Transparent LCD. Manual white balance

f/1.8, 1/100 s.

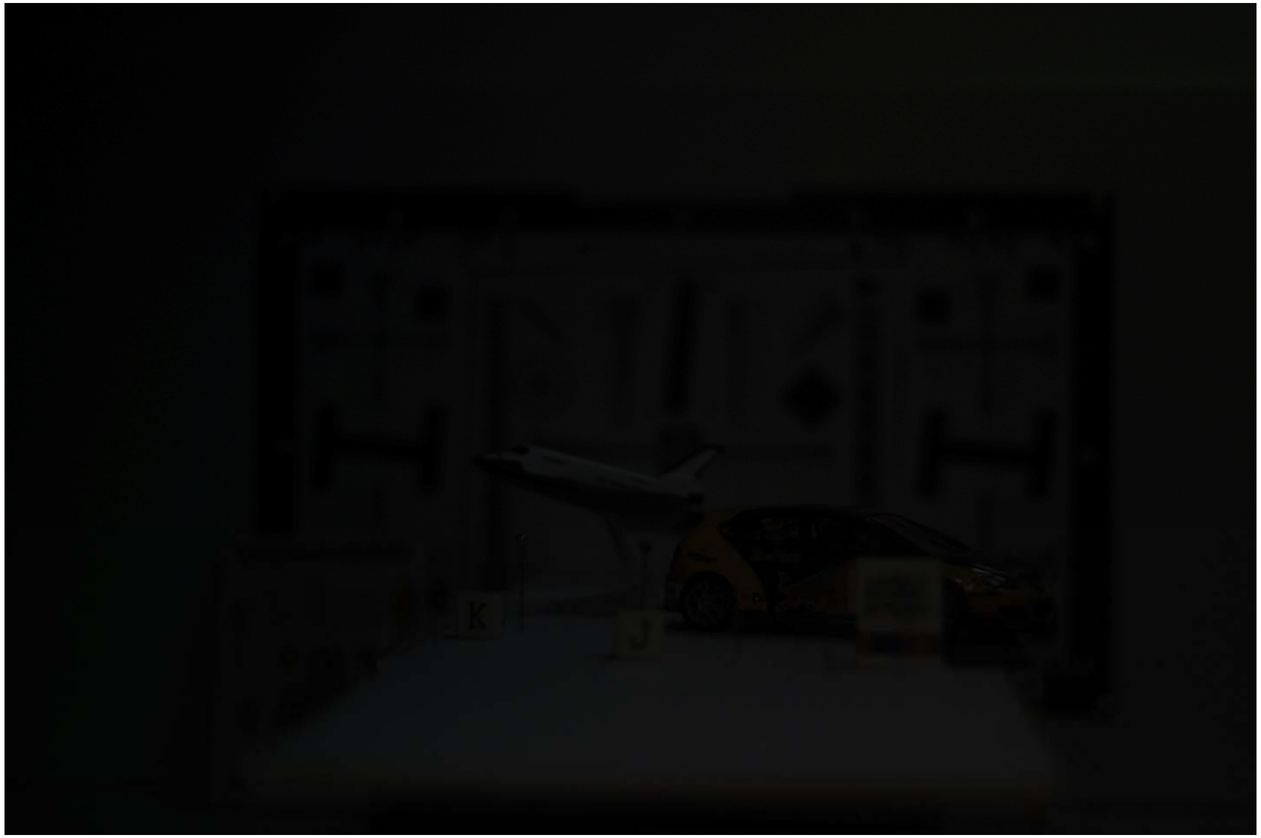
VII. Our prototype

No LCD

LCD in mode transparent

VII. Our prototype

- Black LCD



f/1.8, 1/100 s.

VII. Our prototype

- Small aperture

f/1.8, 1/8 s.

VII. Our prototype

- Small aperture under the previous one

f/1.8, 1/8 s.

VII. Our prototype

- Small aperture (both)

f/1.8, 1/15 s.

VII. Our prototype

- (Pseudo) random aperture

f/1.8, 1/40 s.

Collaborators

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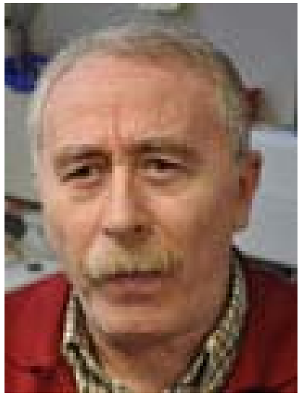

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