Présentation IFPEN, 30 mars 2015

Un imageur compressé utilisant les milieux multiplement diffusants

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Université Paris Diderot - Paris 7
Institut Langevin «Ondes et Images»

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Un imageur compressé utilisant les milieux multiplement diffusants

ou "La vérité si je m'embrouille"

Laurent Daudet

et I. Carron, G. Chardon, S. Gigan, O. Katz,
G. Lerosey, A. Liutkus, D. Martina, S. Popoff

Notion de mesure

Mesurer : Déterminer une quantité ou une grandeur en la comparant à une quantité ou une grandeur de même nature prise comme référence.

Dictionnaire Académie (9è Ed)

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Notion relative a une référence, quantitative : on obtient un nombre

Notion de mesure en physique

Tous les objets physiques se laissent-ils décrire par des nombres ?

Décrire un objet: posséder un modèle (a priori) puis mesurer le ou les paramètre(s) de ce modèle

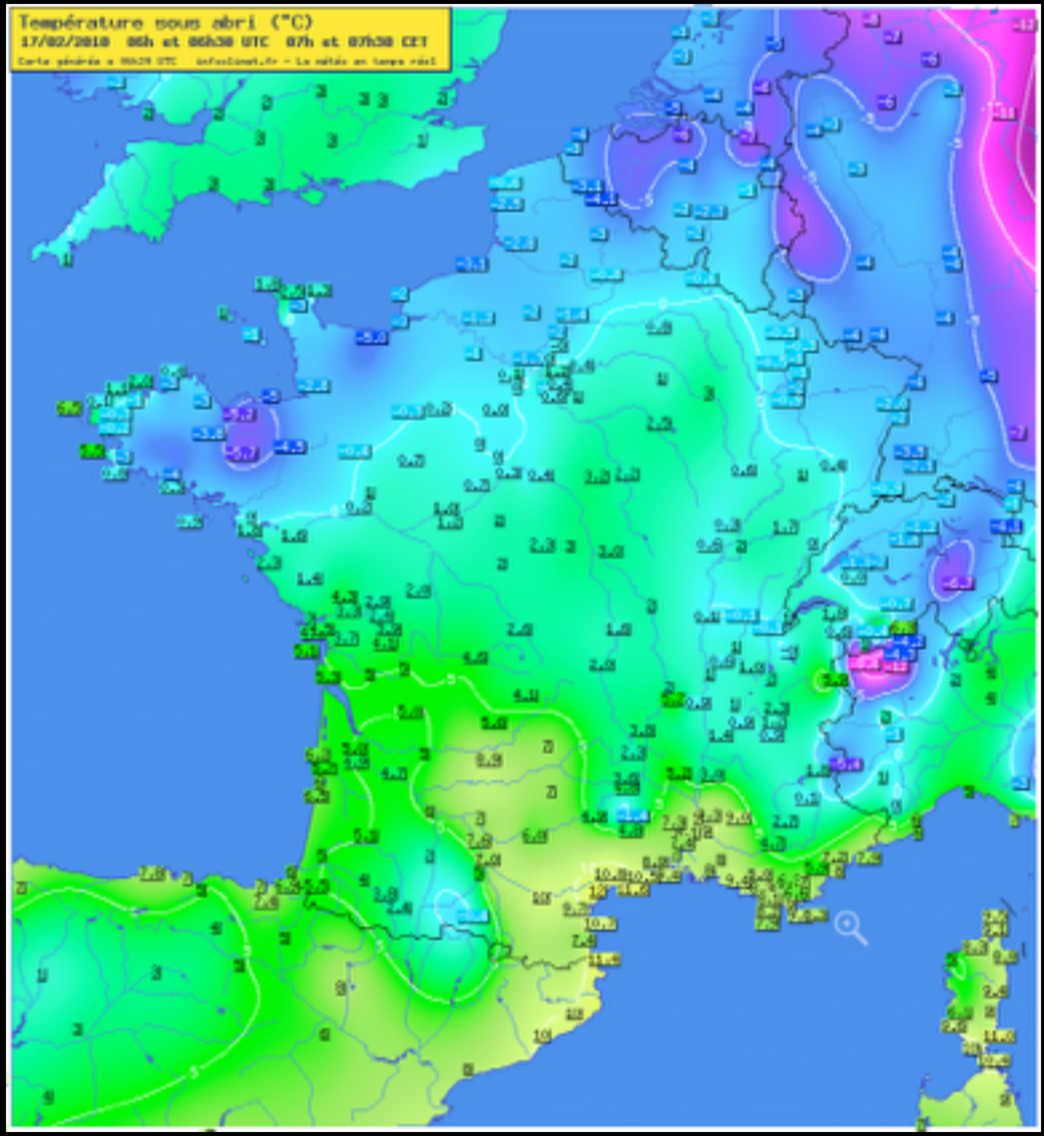
Plus on a d’a priori, moins on a besoin de mesurer.

Exemple : les moutons de Dirac

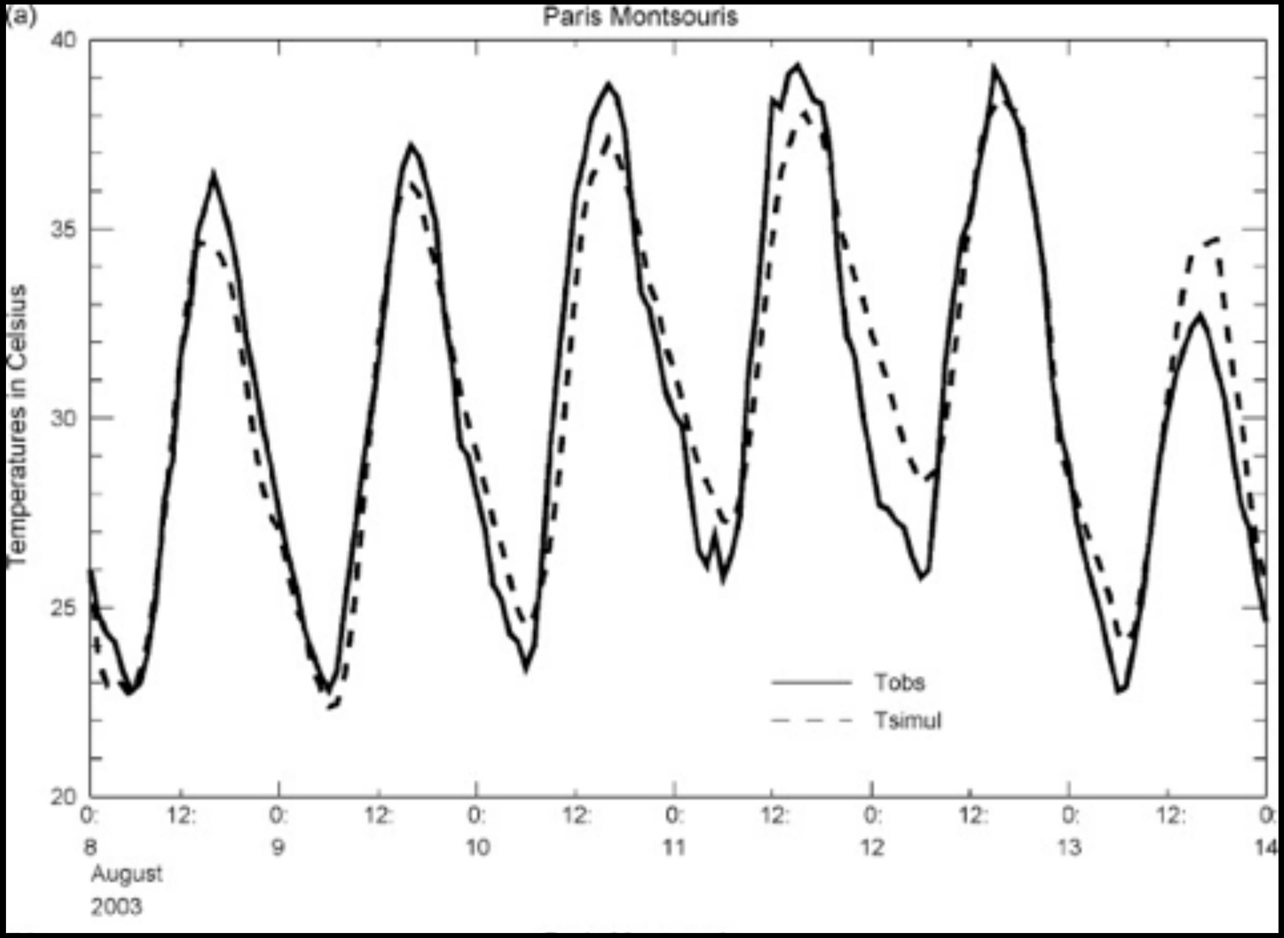
Echantillonnage : pour mesurer le continu

Problème des objets dépendant de paramètres continus : exemple temps, espace

Ex température = T(latitude, longitude, temps)



www.infoclimat.fr



http://www.sciencedirect.com/science/article/pii/S1631071307002015

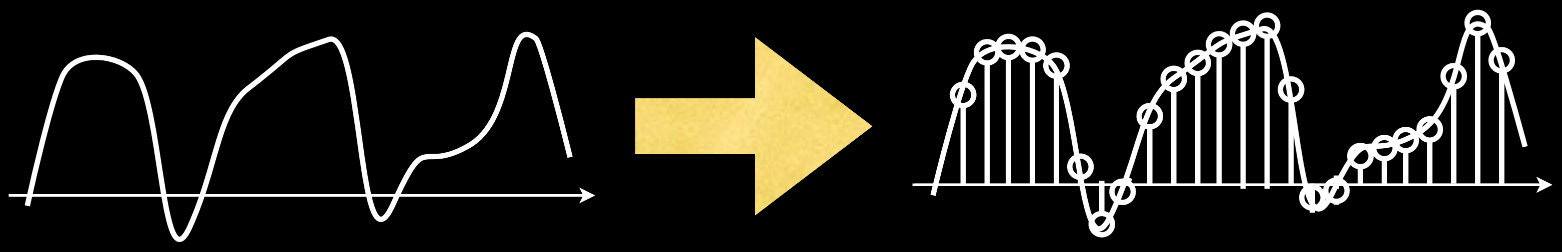
Echantillonnage : pour mesurer le continu

Comment connaitre la T partout en France alors que l'on n'est pas capable de la mesurer partout ?

Problème théorique d'*échantillonnage* (notion utile aussi en satistique : connaitre le tout en ne mesurant qu'une partie)

Problème concret de *numérisation* : on peut pas manipuler une infinité de nombres sur un ordinateur (par ex pour images, sons, etc ...)

Echantillonnage version 40’s - 50’s



Si les variations ne sont pas trop rapides, la courbe est entièrement déterminée par des échantillons régulièrement espacés

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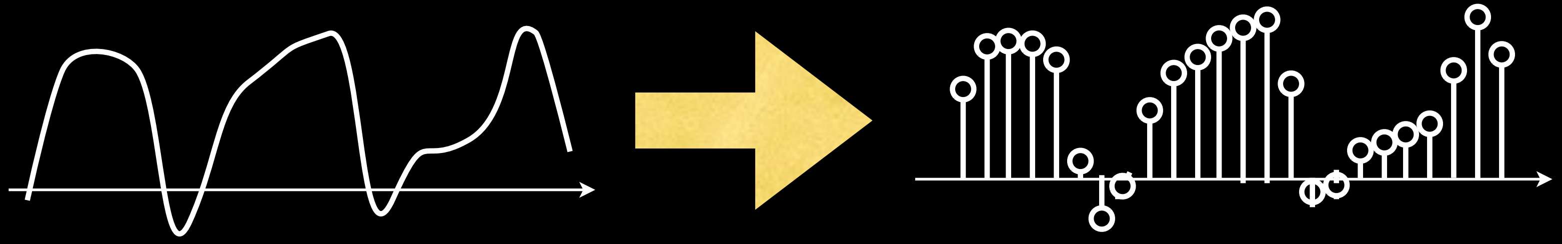


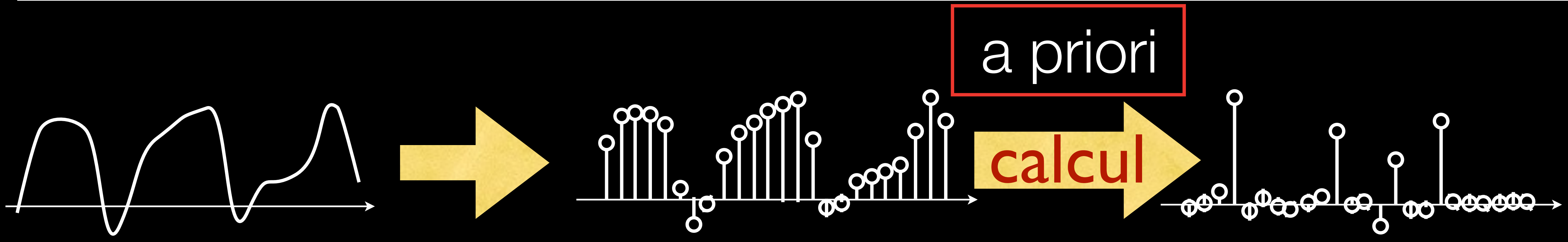
Si les variations ne sont pas trop rapides, la courbe est entièrement déterminée par des échantillons régulièrement espacés

Lien entre distance entre échantillons et variations du signal : $f_e > 2\ f_{max}$

Shannon-Nyquist-Whittaker-Kotelnikov-Raabe

Reconstruction *linéaire* à partir des échantillons

Traitement des signaux version 80's - 90's



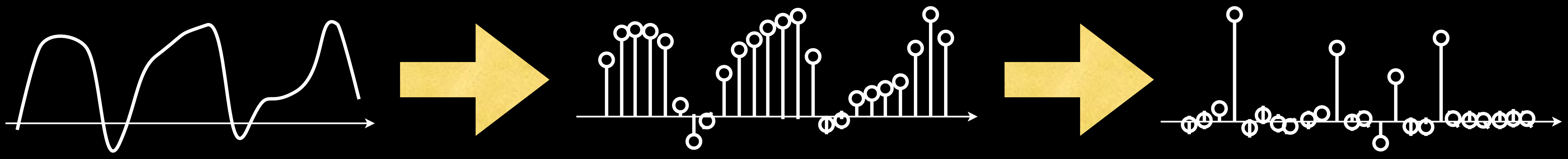
Par changement de base (ou dans une base redondante), la plupart des signaux naturels sont « parcimonieux » :

peu de gros coefficients, beaucoup de très petits

Permet le débruitage, le codage, etc ...

Nécessite un *a priori* sur quelle est la base appropriée

Exemple : la musique

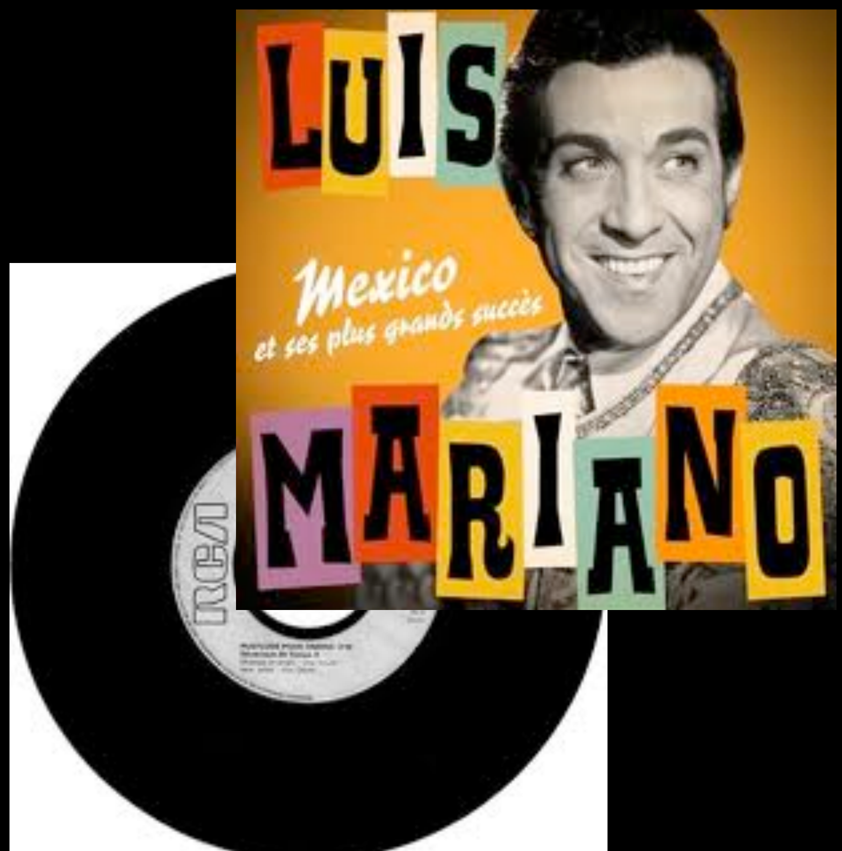


0101001101001010101110011100
0101010101011100111001001010
1110000101010001010100111000
0001100100010101110011101010
1100111011001010111001100100
1100111011001010111001100100
1100111011001010111001100100

01010011010010
10101110011100
01010101010111

p(t)

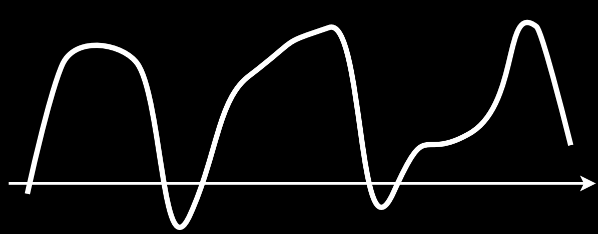
analogique

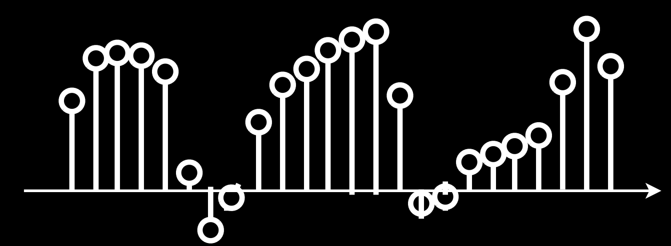


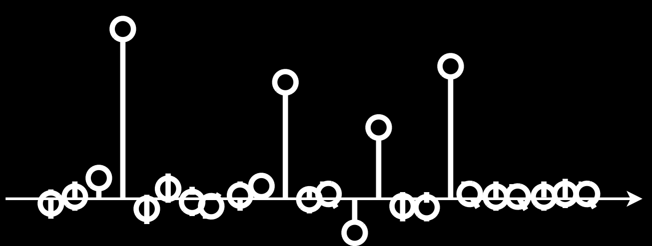
CD

MP3

Exemple : les images







0101001101001010101110011100
0101010101011100111001001010
1110000101010001010100111000
0001100100010101110011101010
1100111011001010111001100100
1100111011001010111001100100
1100111011001010111001100100

01010011010010
10101110011100
01010101010111

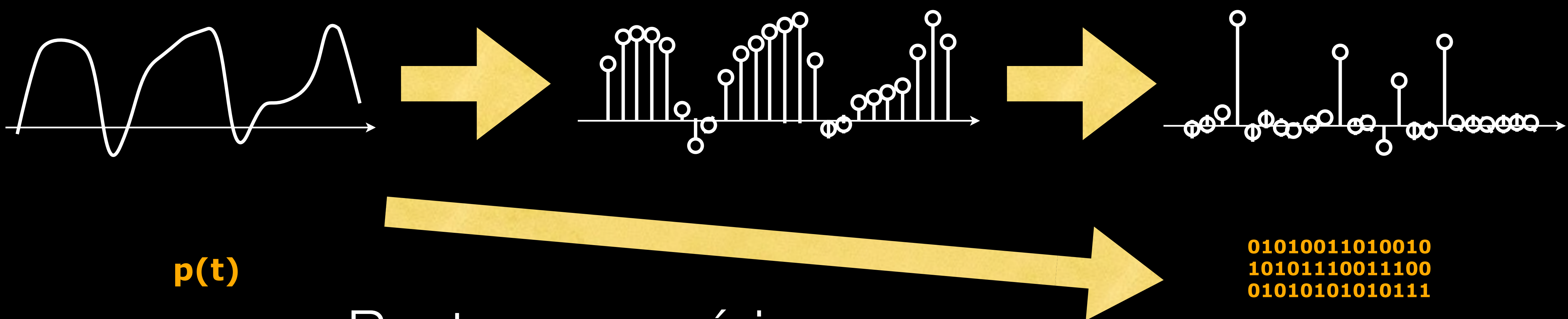
I(x,y)

argentique

numérique
RAW

numérique
JPG

Les années 2000-2010:
Echantillonnage compressé



Peut-on acquérir directement dans le domaine compressé ?

Candès, Donoho (2006) : OUI si le sigal est parcimonieux dans une base B1 ET si on acquiert dans une base B2 incohérente avec B1

Bonne manière d'obtenir l'incohérence : le **hasard** !

Echantillonnage compressé

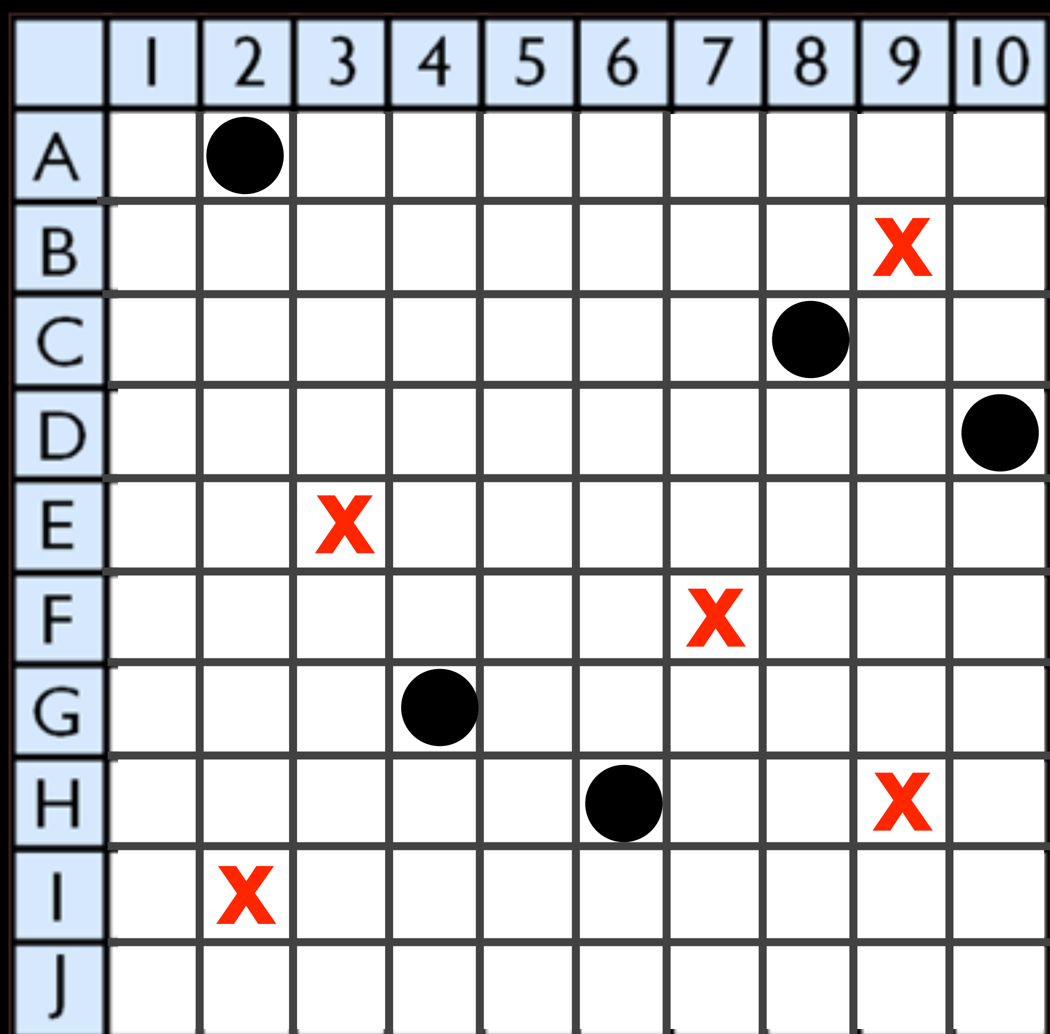
Exemple : la bataille navale !

Echantillonnage compressé

Exemple : la bataille navale !

Echantillonnage compressé

Exemple : la bataille navale

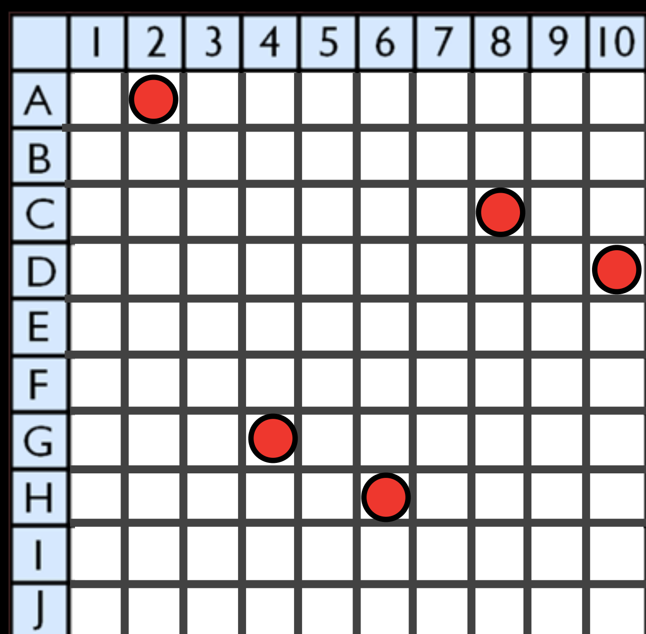


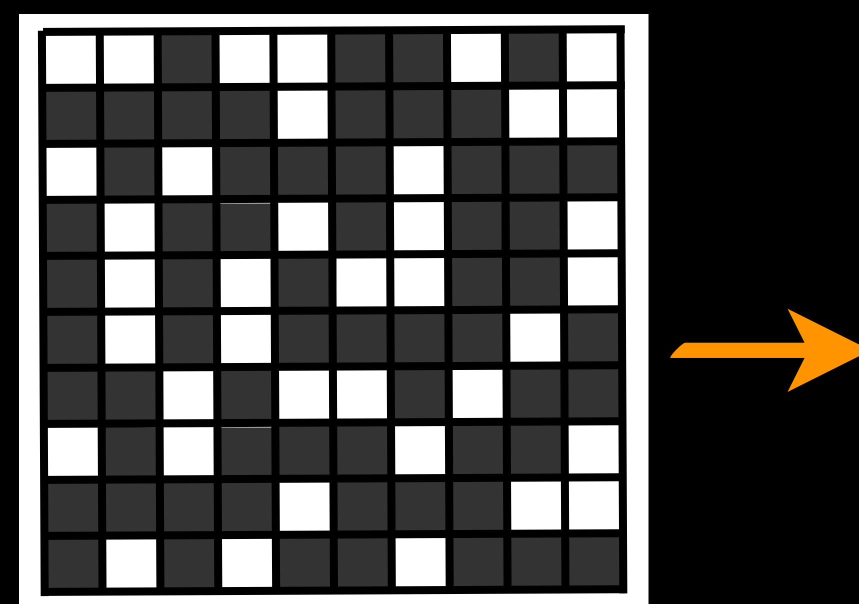
Retrouver la position des 5 bateaux en posant le moins de questions possibles

(ici en moyenne il faut en 85 questions)

Echantillonnage compressé

Exemple : la bataille navale





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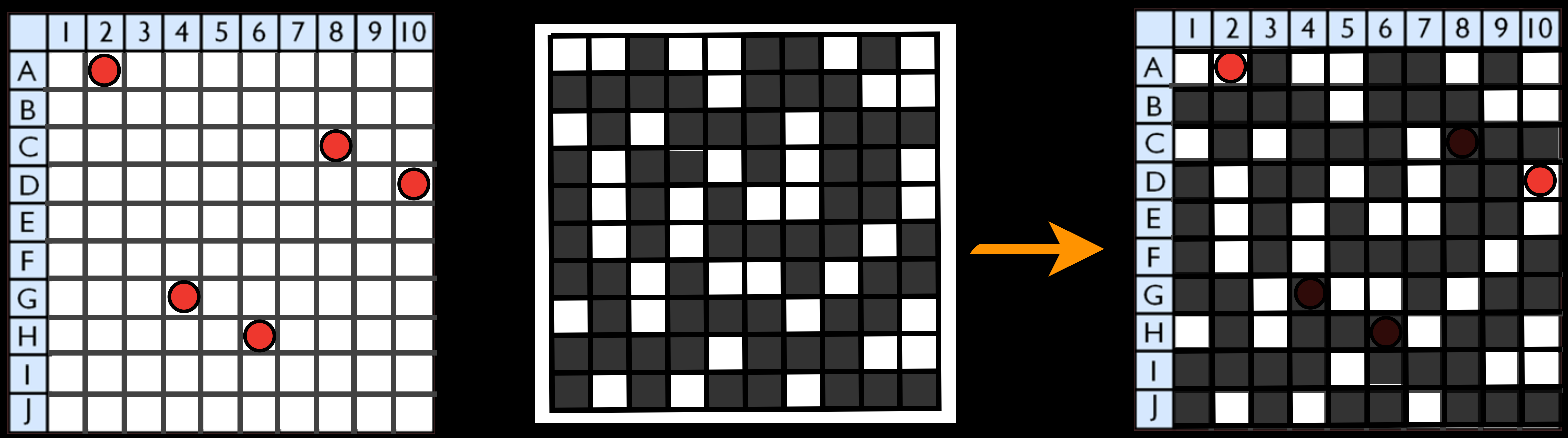

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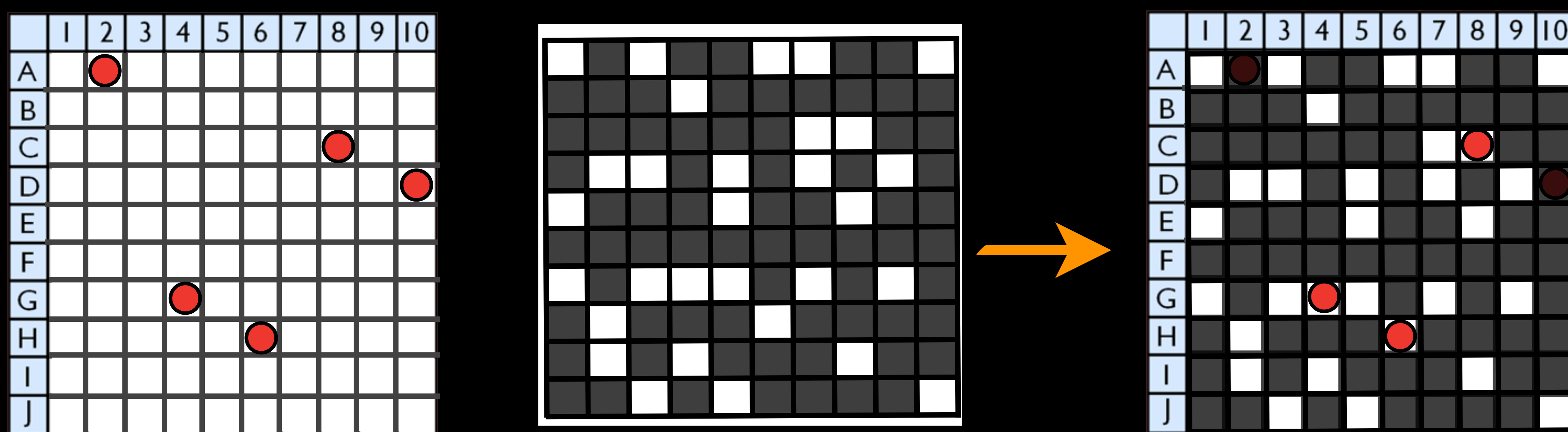
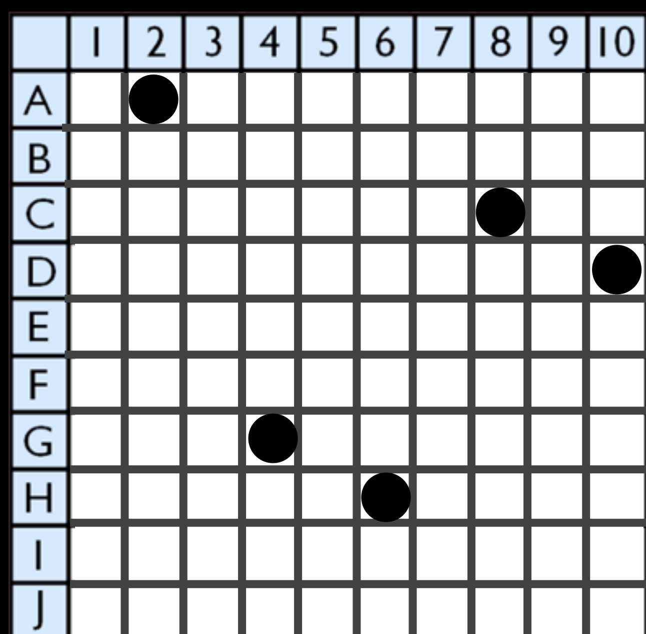


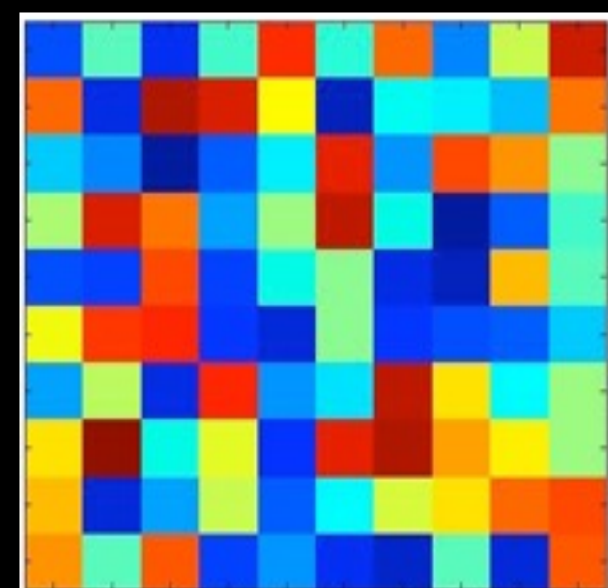
Echantillonnage compressé

Exemple : la bataille navale

$\sum$



$.*$

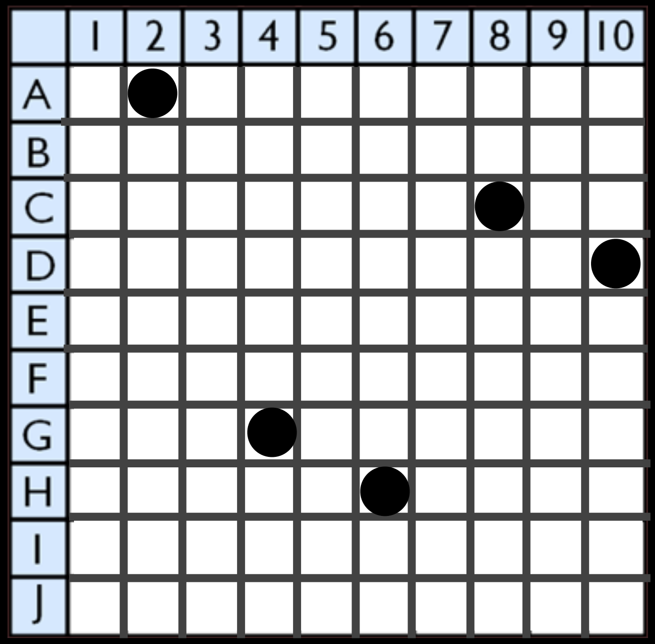


$= m_1$

Echantillonnage compressé

Exemple : la bataille navale

$\sum$



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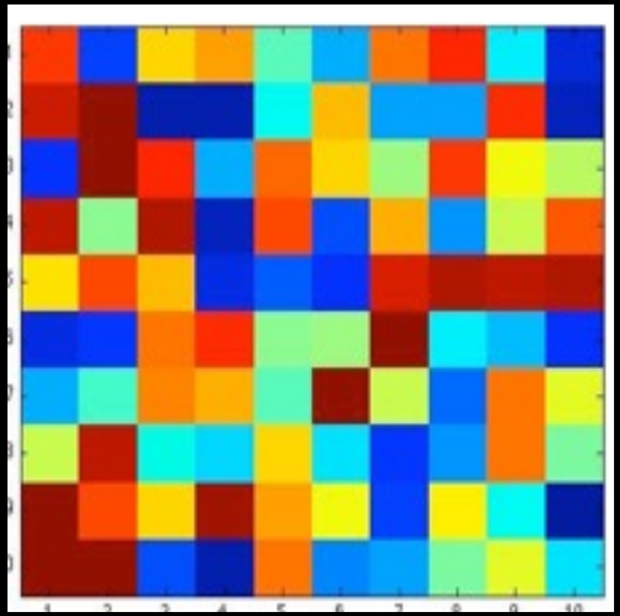
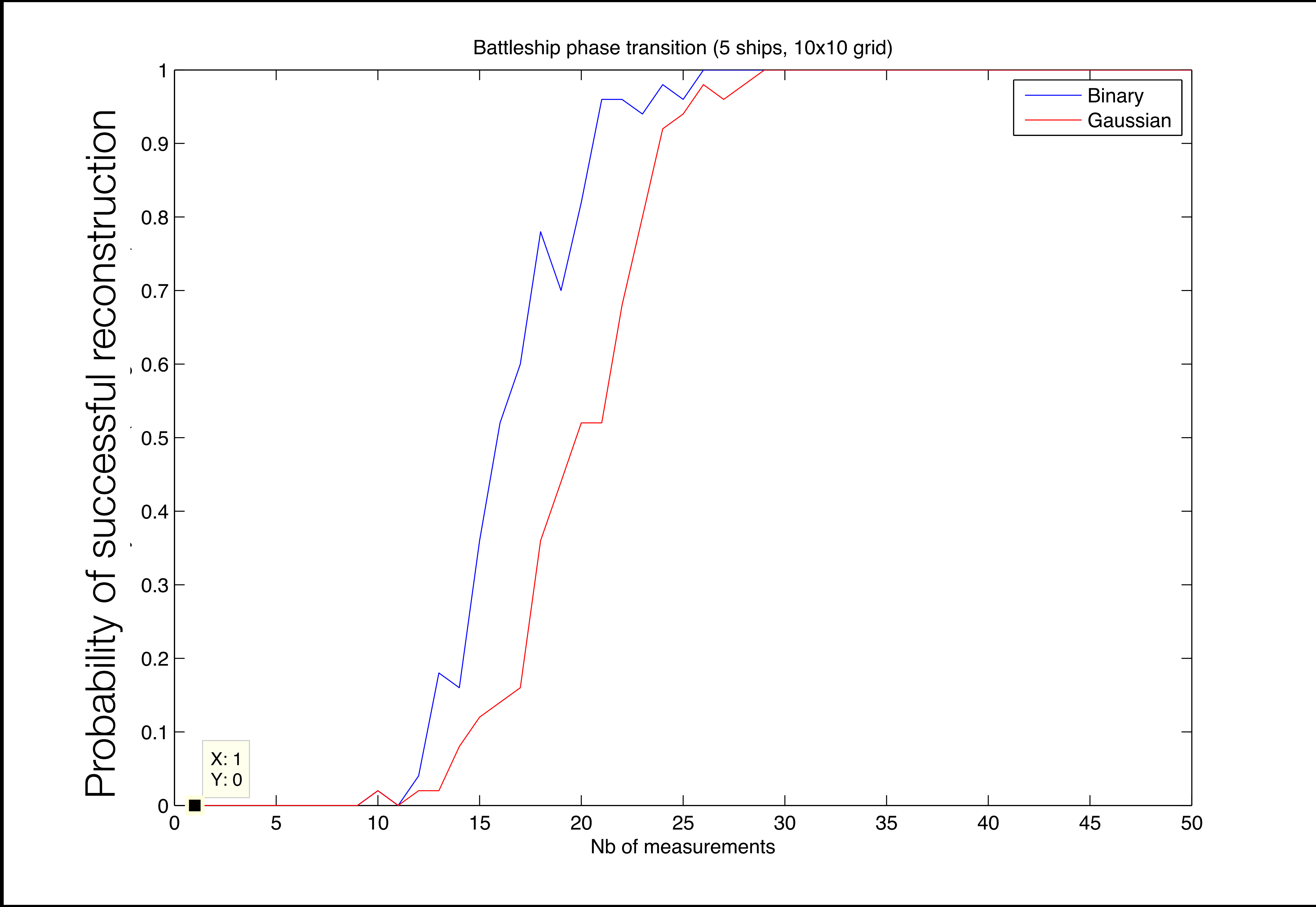


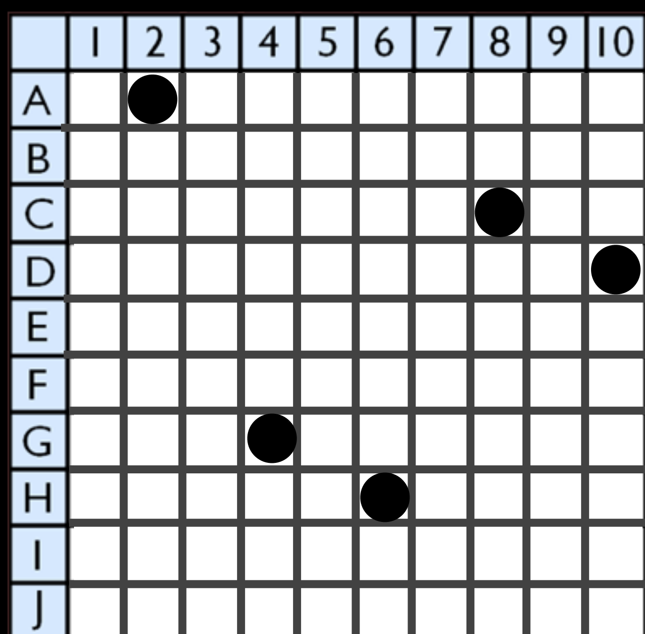
$= m_2$

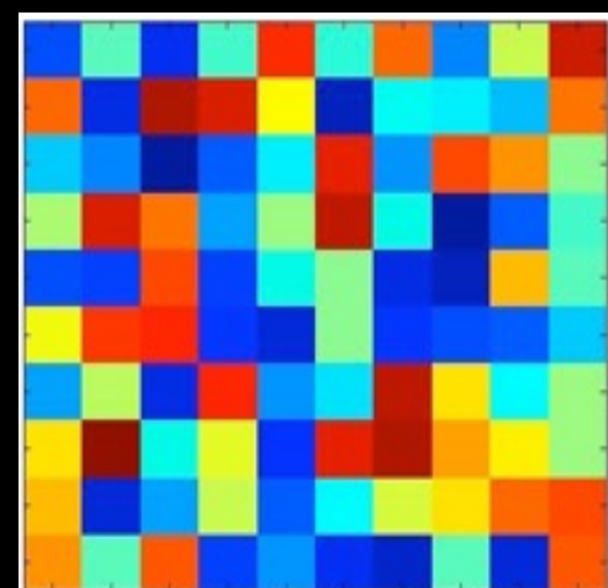
Echantillonnage compressé



Echantillonnage compressé

Exemple : la bataille navale





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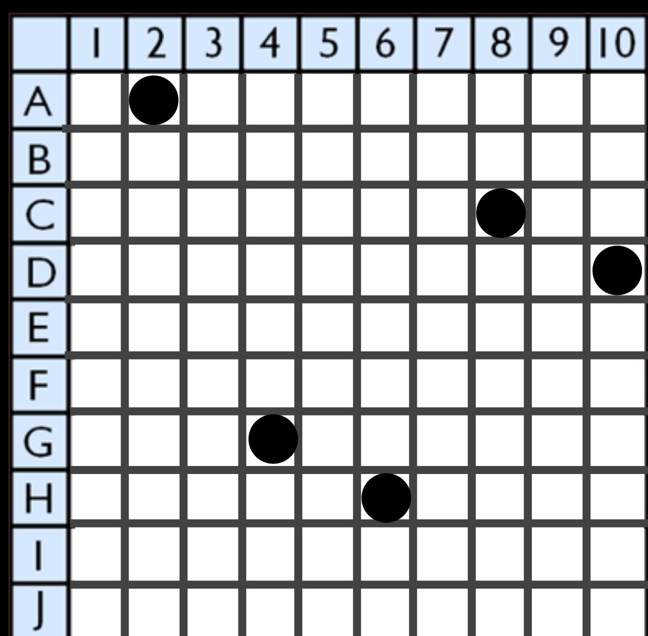

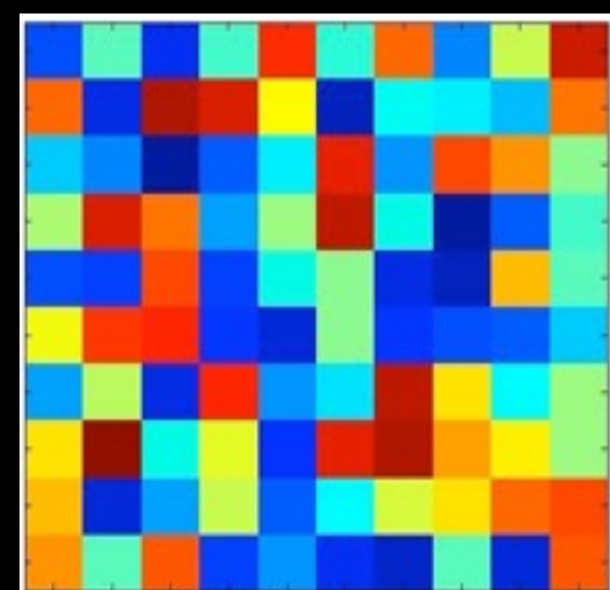

échantillonnage standard, nombre questions ~ nb cases

Echantillonnage compressé

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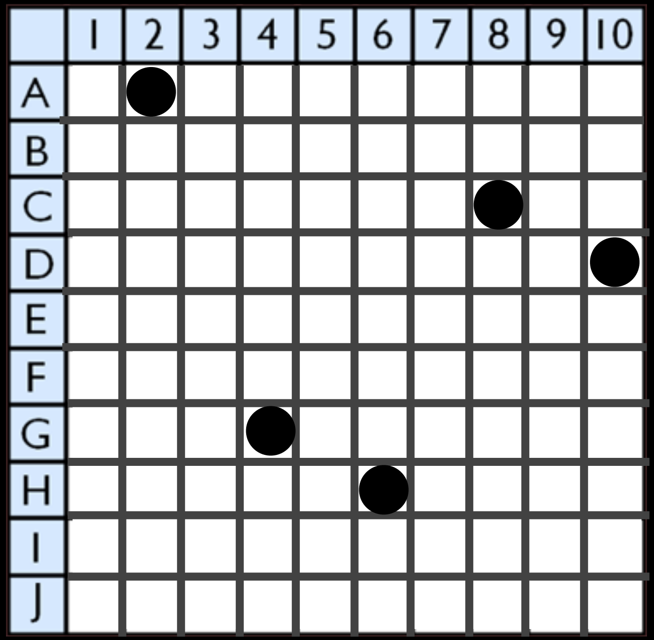

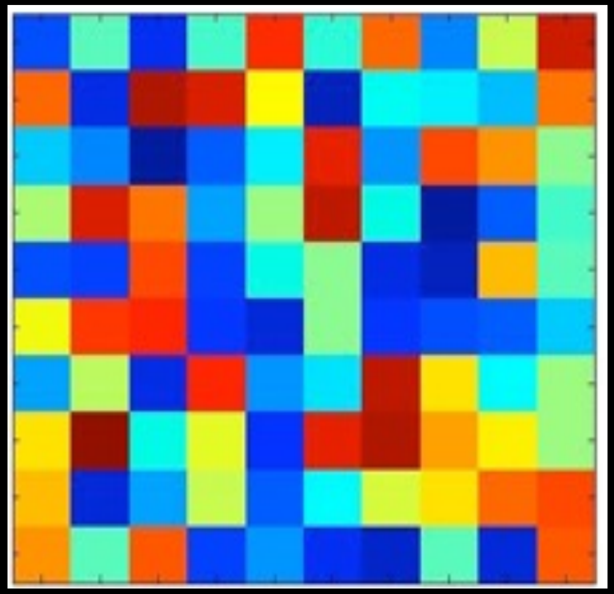

échantillonnage standard, nombre questions ~ nb cases

échantillonnage compressif, nombre bateaux << nb cases

Echantillonnage compressé

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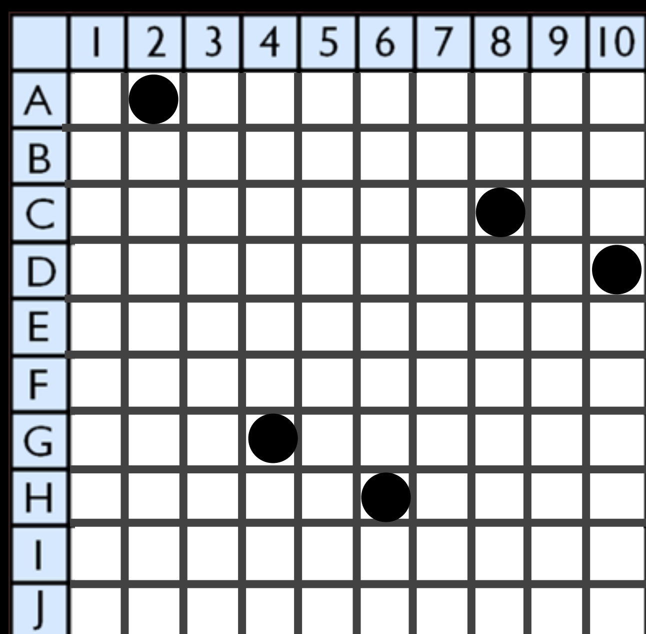
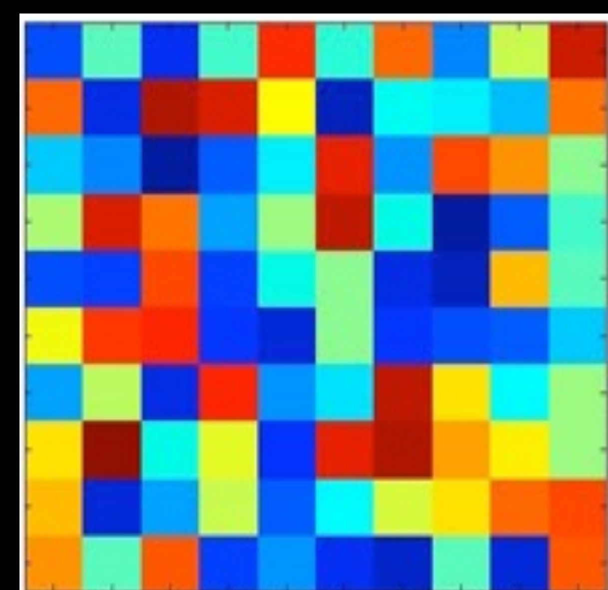




échantillonnage standard, nombre questions ~ nb cases

échantillonnage compressif, nombre bateaux << nb cases

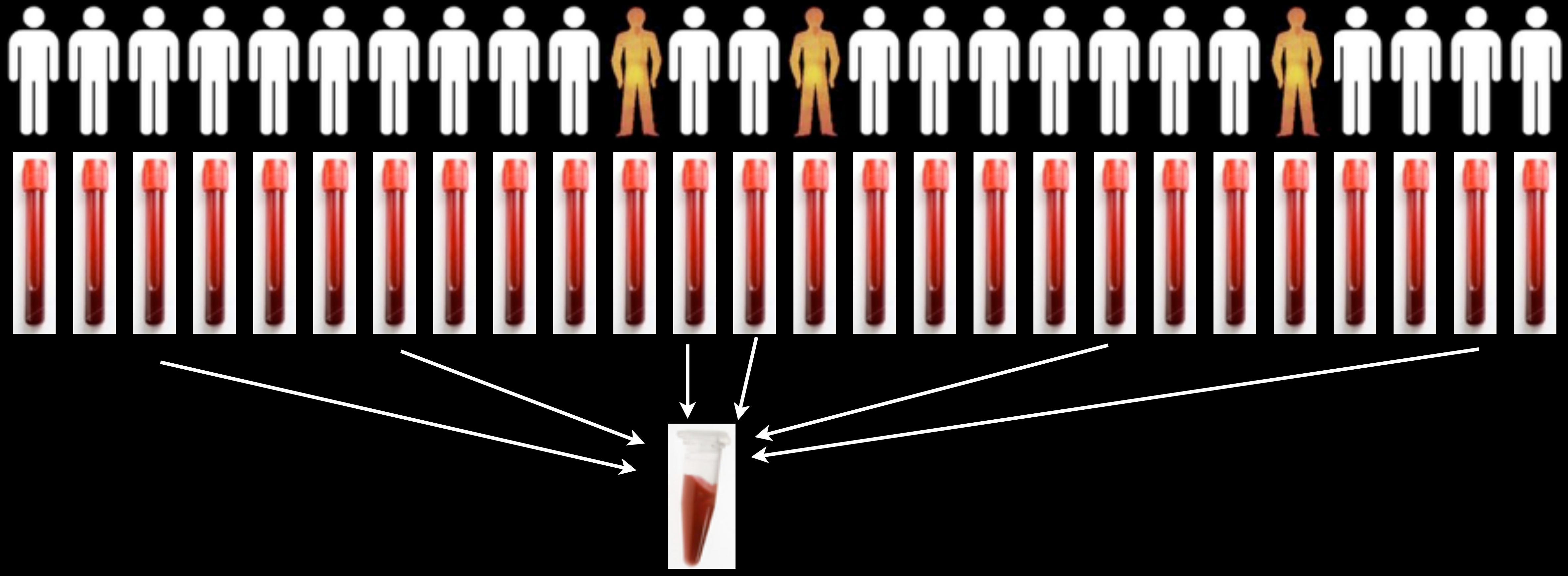
avec dépendance en log(N) sur le nombre de cases

Echantillonnage compressé

- **Démocratique :** Chaque mesure donne de l'information sur la totalité du signal (toutes les mesures sont également informatives)

- **Universel :** avec des mesures aléatoires, on mesure de façon incohérente quelle que soit la base de parcimonie.

Lien avec le «group testing»



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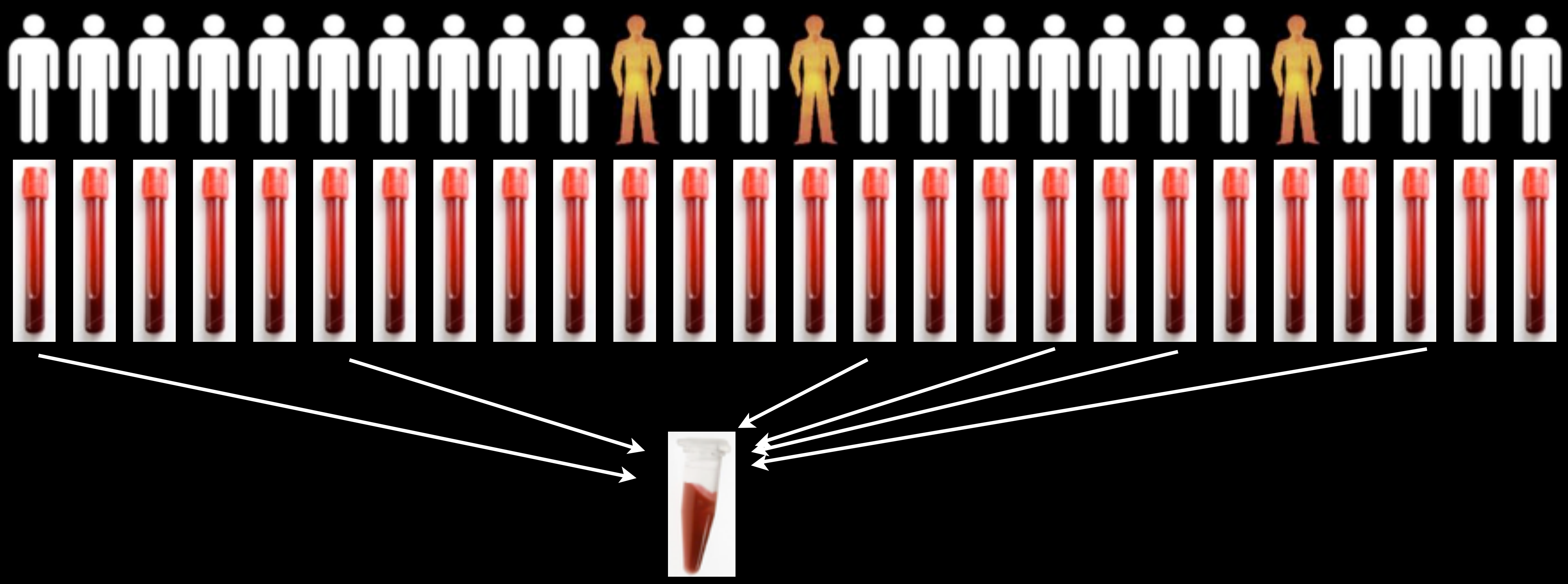
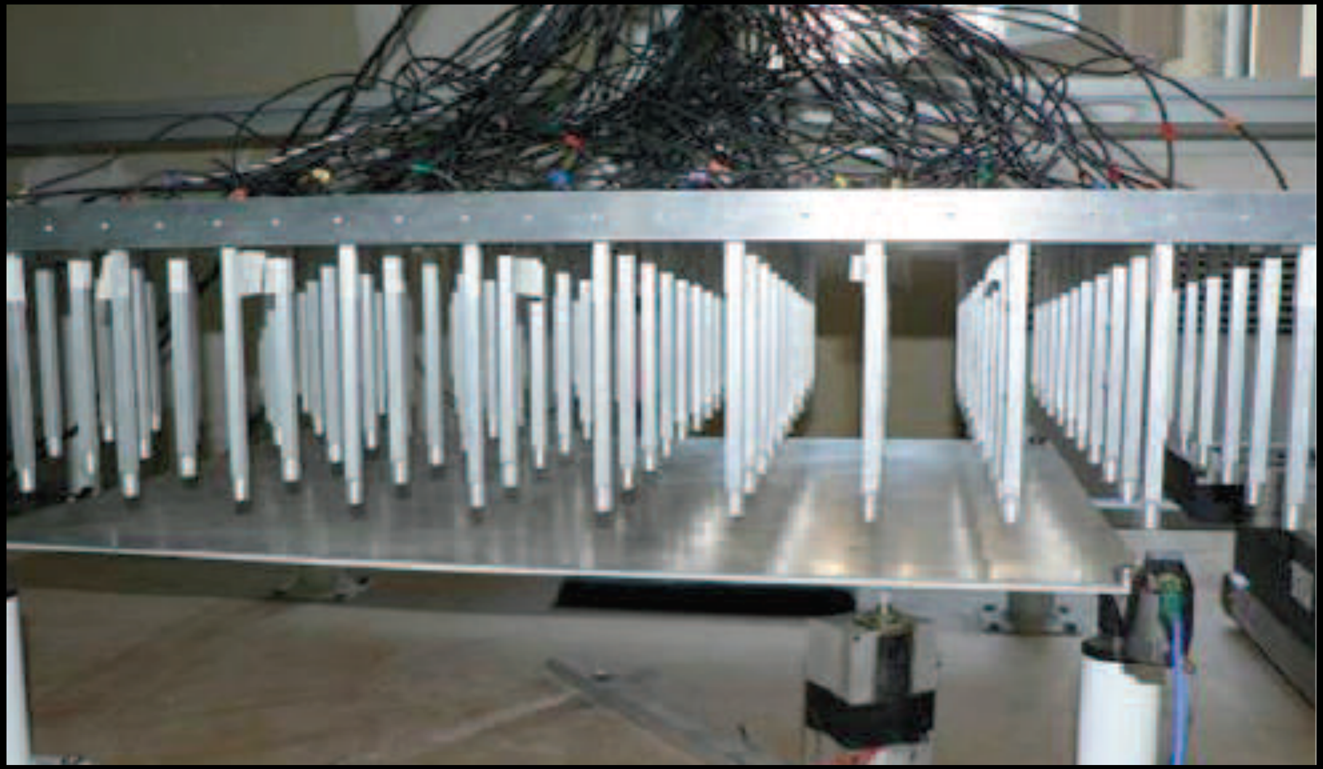
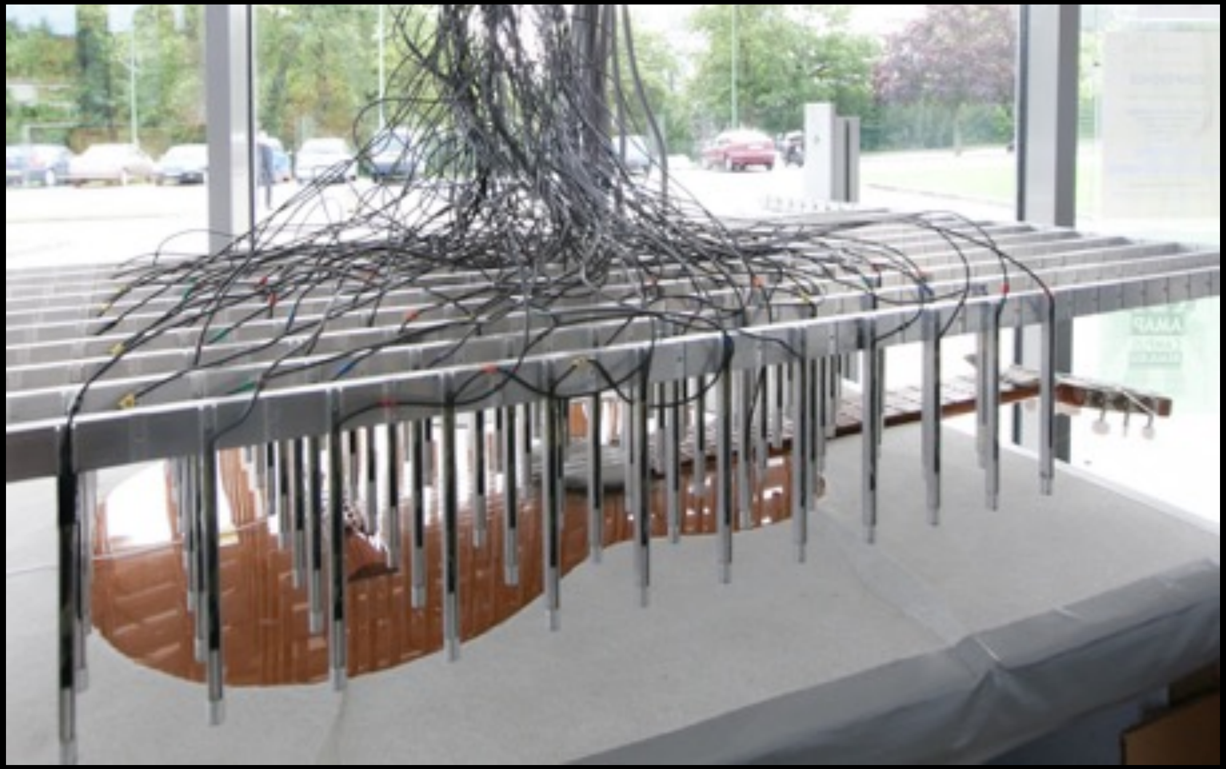


Echantillonnage compressé en acoustique

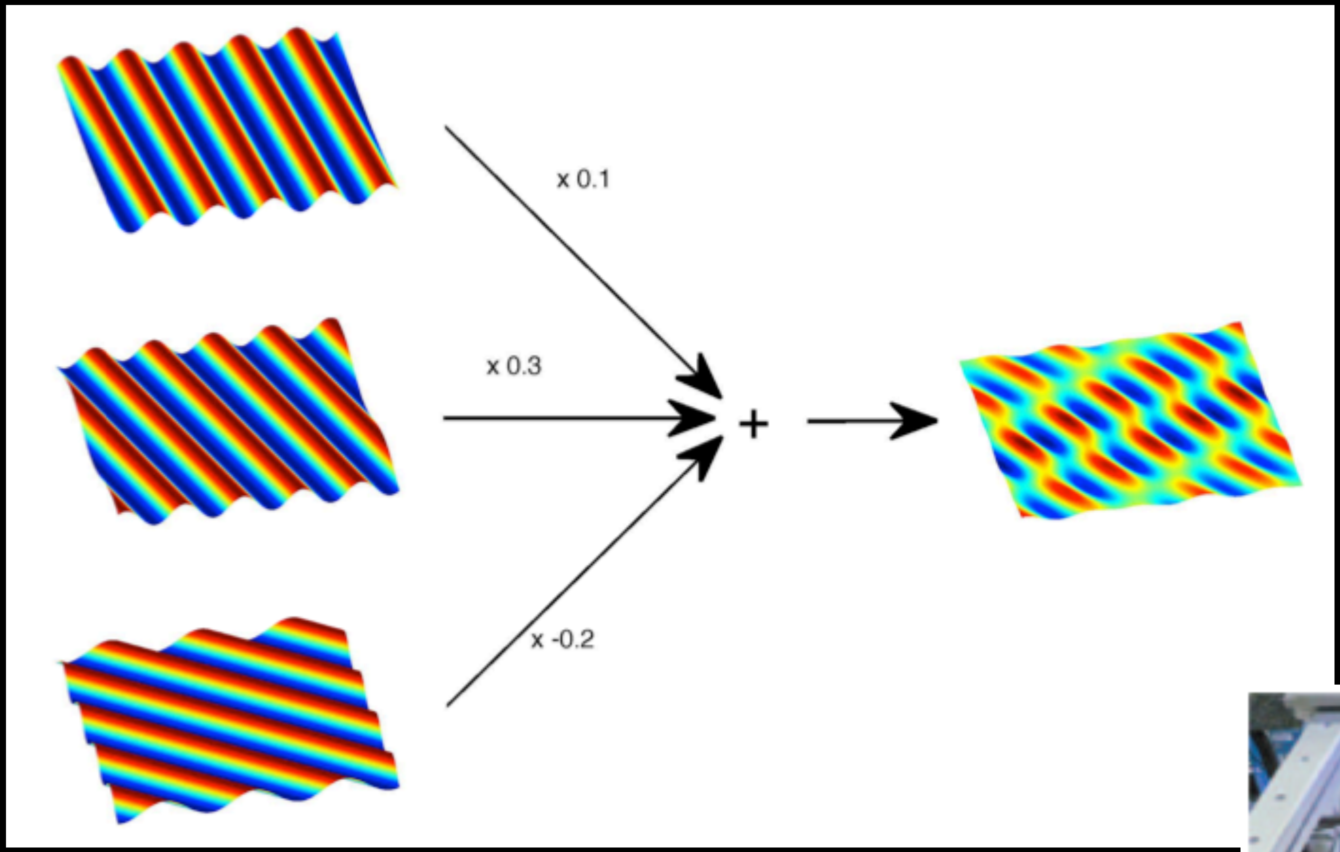
Holographie Acoustique en Champ Proche

But : comprendre les modes de vibration de plaques vibrantes (tables d’harmonie de guitare par ex).

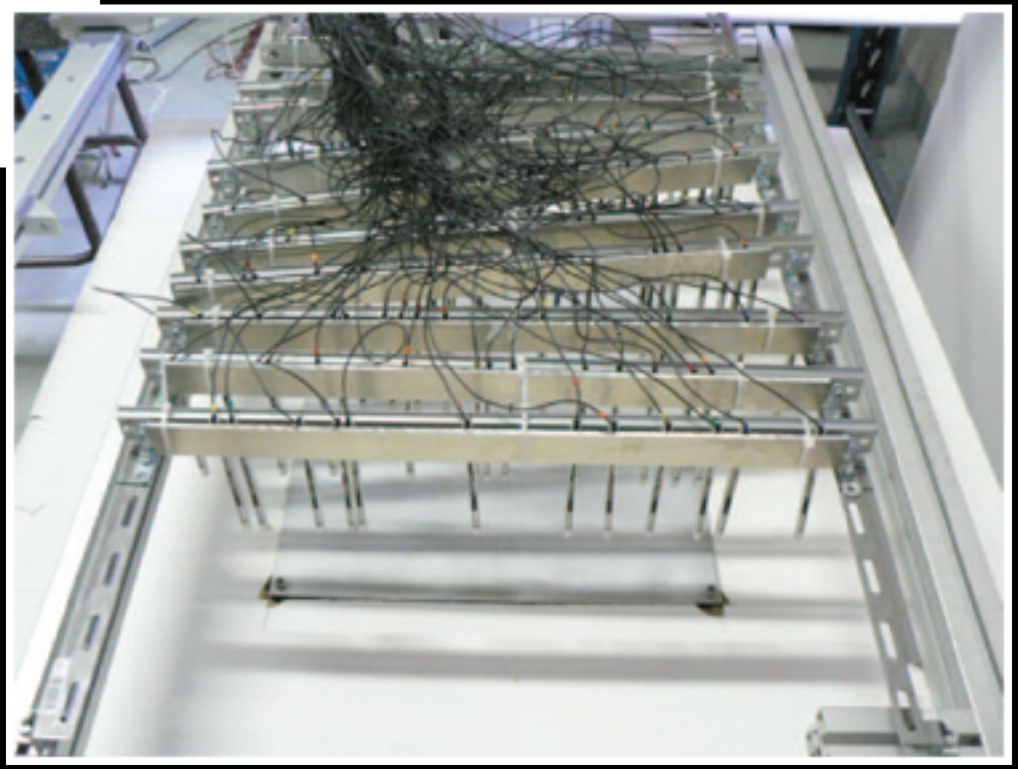




Echantillonnage compressé en acoustique



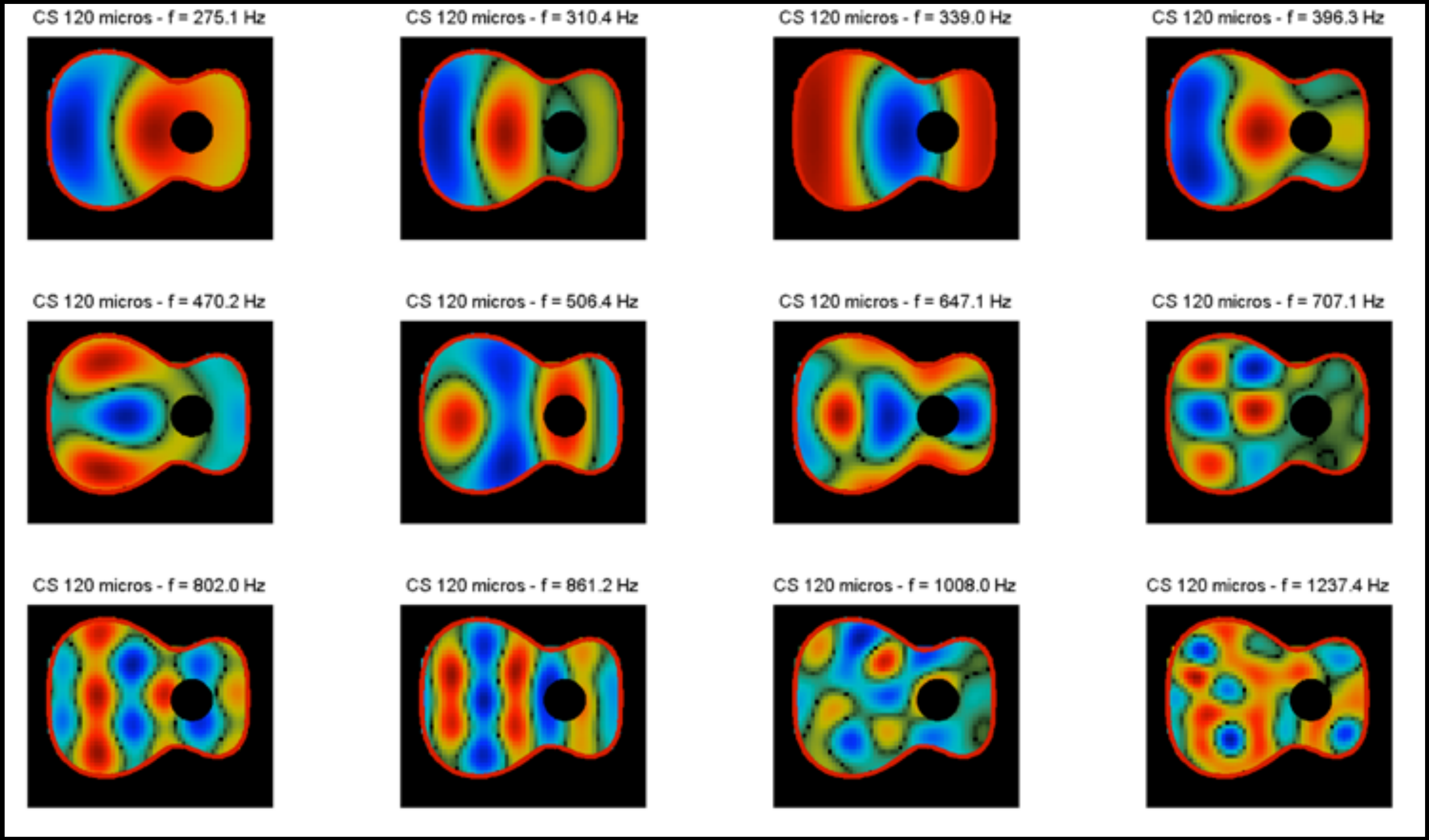
La parcimonie des vibrations dans une base approprié ...



... suggère d'utiliser une antennes à positions de micros aléatoires

Echantillonnage compressé en acoustique

Réduction drastique du nombre de mesures nécessaires !



The one-pixel camera

If natural images are sparse, are there better sampling schemes than 20 Mpixel regular sensors as in digital cameras ? (where 99% of images end up as JPEGs)

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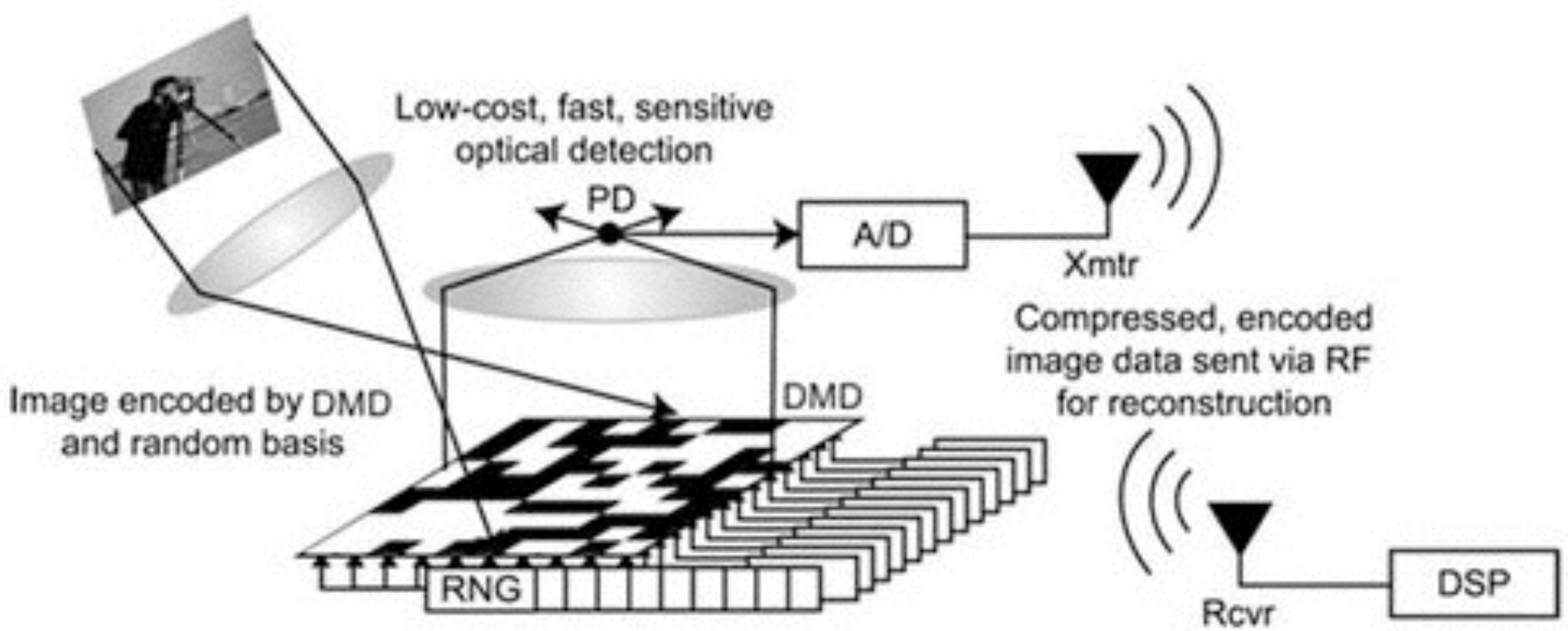

(Baraniuk team, Rice Univ.)

Beyond the single-pixel camera

- Information scrambling by randomness is provided by carefully-engineered hardware (as are other similar schemes based on coded aperture)
- Measurements are performed sequentially (slow)

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Can we make it simpler / faster ?

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- Measurements are performed sequentially (slow)

Can we make it simpler / faster ?

Use randomness provided by Nature in **multiply scattering materials**

Scattering : a coherent process

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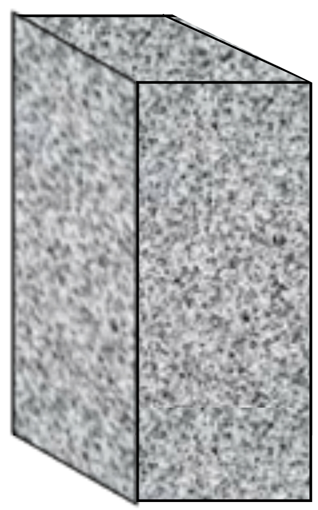
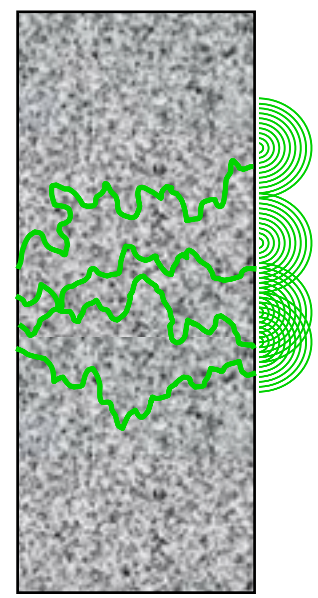
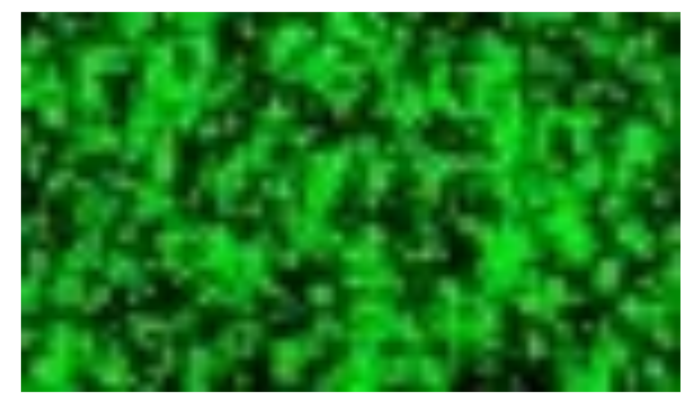
Volume scattering:

Coherent light
(laser)



thin layer (about 300 μm)
of white paint
(particle size $\leq$ 1 μm)

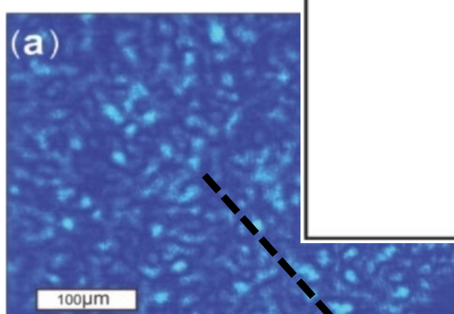


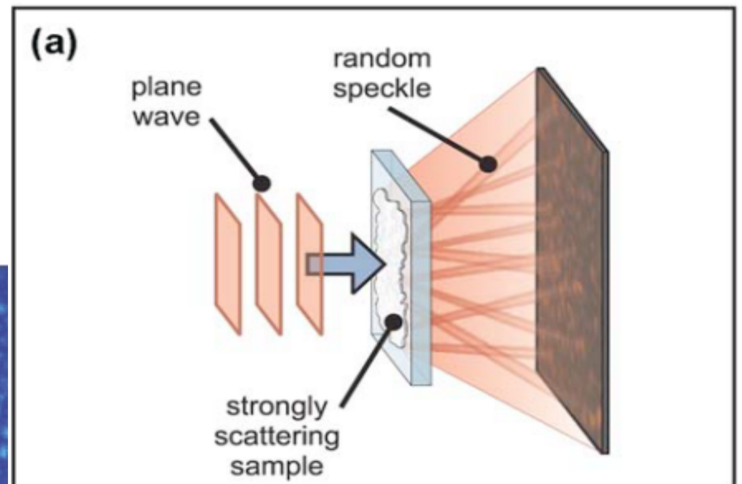


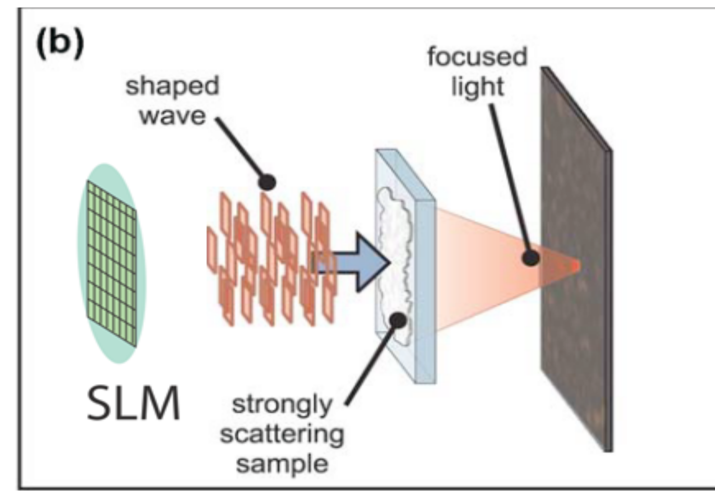
Speckle results from multiple interference
between a multiplicity of random paths

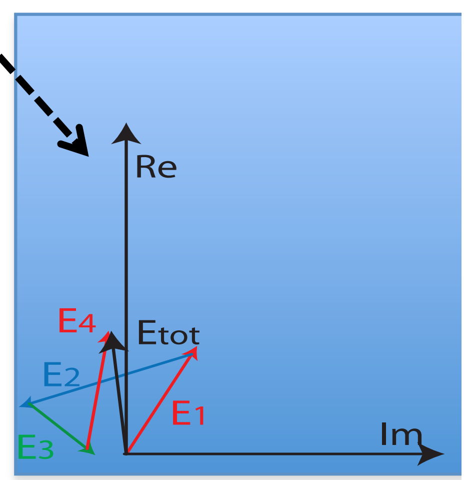
Optimization for focusing through complex media

IM Vellekoop and AP Mosk, Optics Letters, 32(16) 2007









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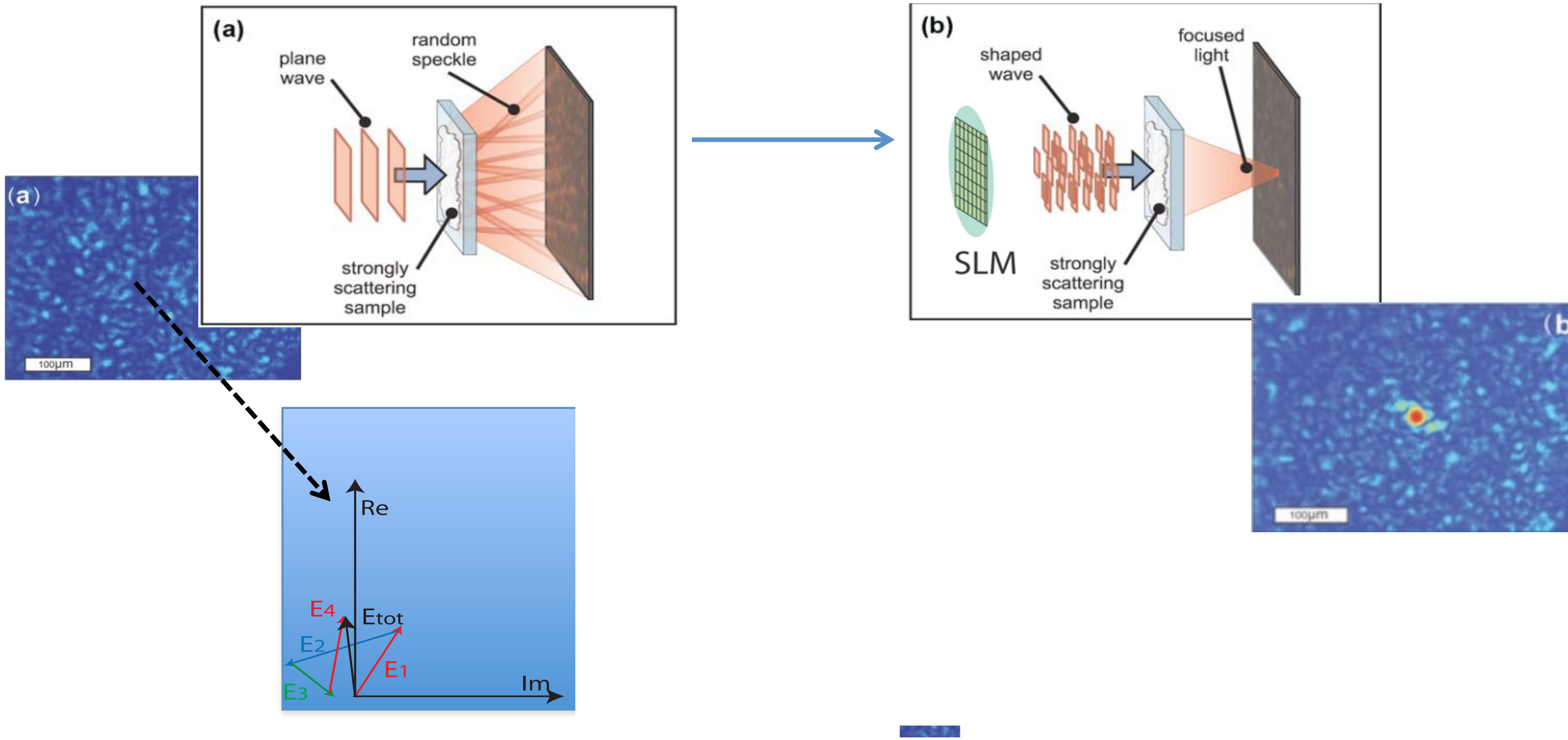
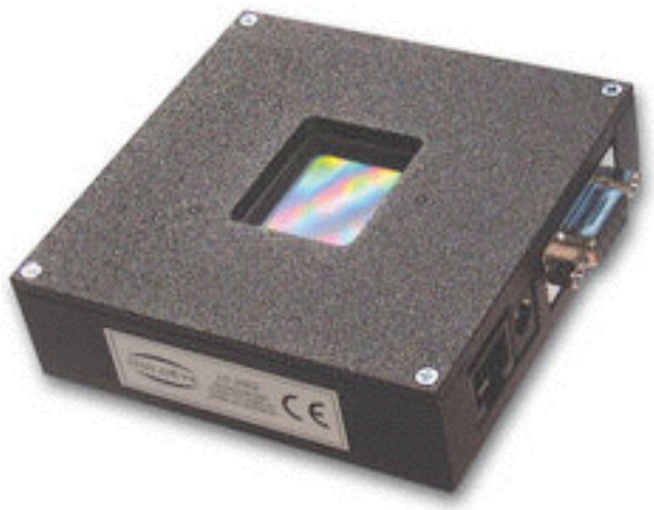


It is possible to shape these modes in phase to obtain a constructive interference on a single speckle grain (Equivalent to phase-conjugation)

A more general approach : the transmission matrix

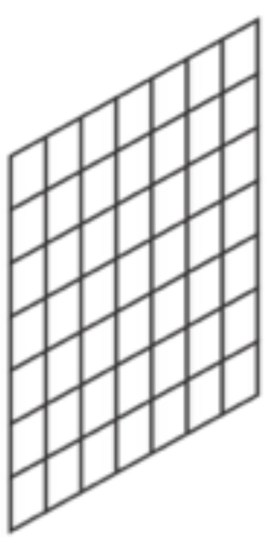
Popoff et al. *Nat. Commun.* 1:81
doi: 10.1038/ncomms1078 (2010)

A more general approach : the transmission matrix



SLM: array of pixels

=



N complex-valued amplitudes

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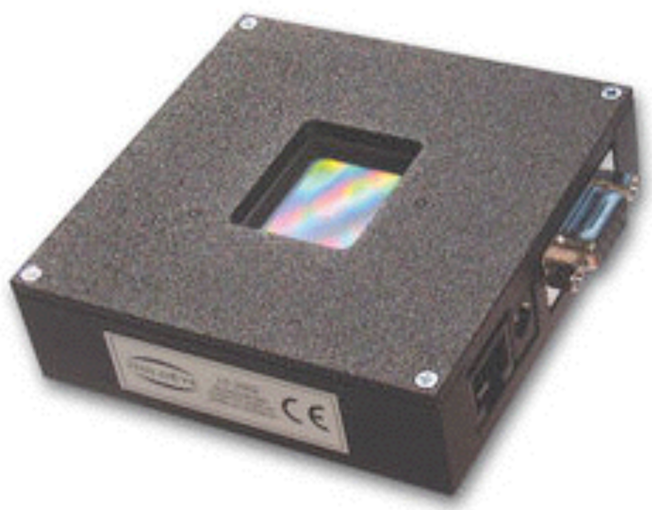

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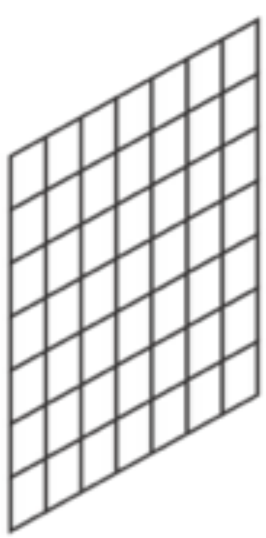

N complex-valued amplitudes

Linear system

=

$$H = \begin{pmatrix} h_{1,1} & h_{1,2} & \dots & h_{1,N} \\ h_{2,1} & h_{2,2} & \dots & h_{2,N} \\ \vdots & & \ddots & \vdots \\ h_{M,1} & h_{M,2} & \dots & h_{M,N} \end{pmatrix}$$

MxN complex-valued matrix

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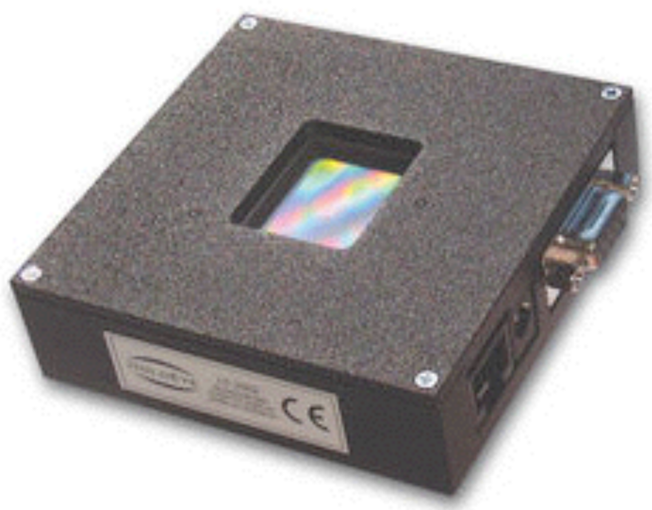
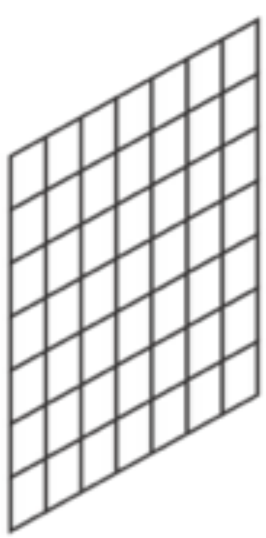


SLM: array of pixels

Linear system

CCD camera: arrays of pixels

=



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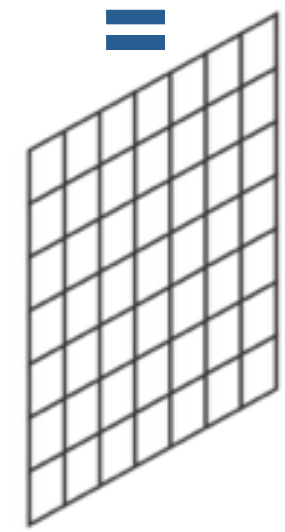
MxN complex-valued matrix

=

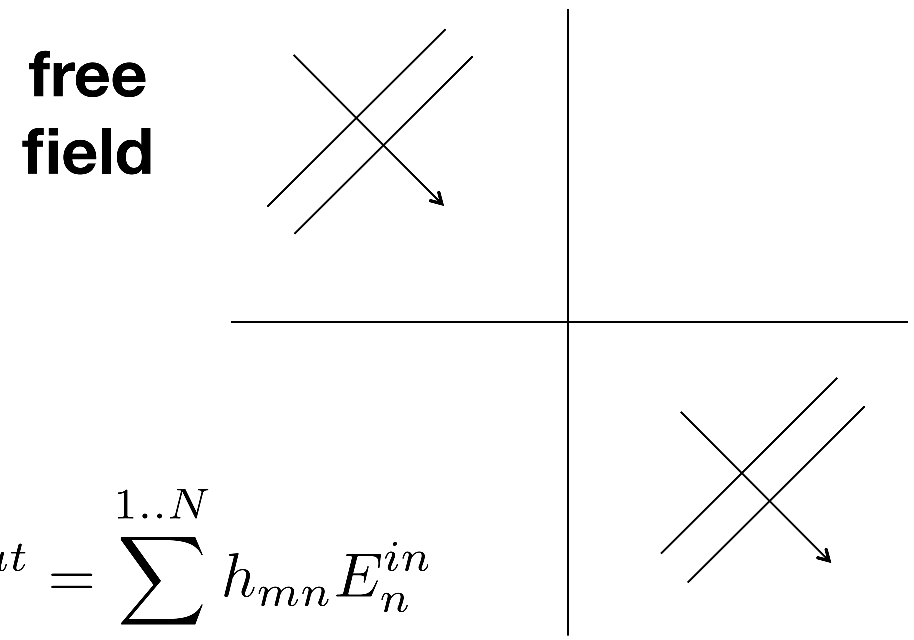


M modulus of complex-valued coefficients

$$\left|E_m^{out}\right| = \left|\sum_n h_{mn} E_n^{in}\right|$$

Popoff et al. *Nat. Commun.* 1:81
doi: 10.1038/ncomms1078 (2010)

A more general approach : the transmission matrix



$$E_m^{out} = \sum_{n}^{1..N} h_{mn} E_n^{in}$$

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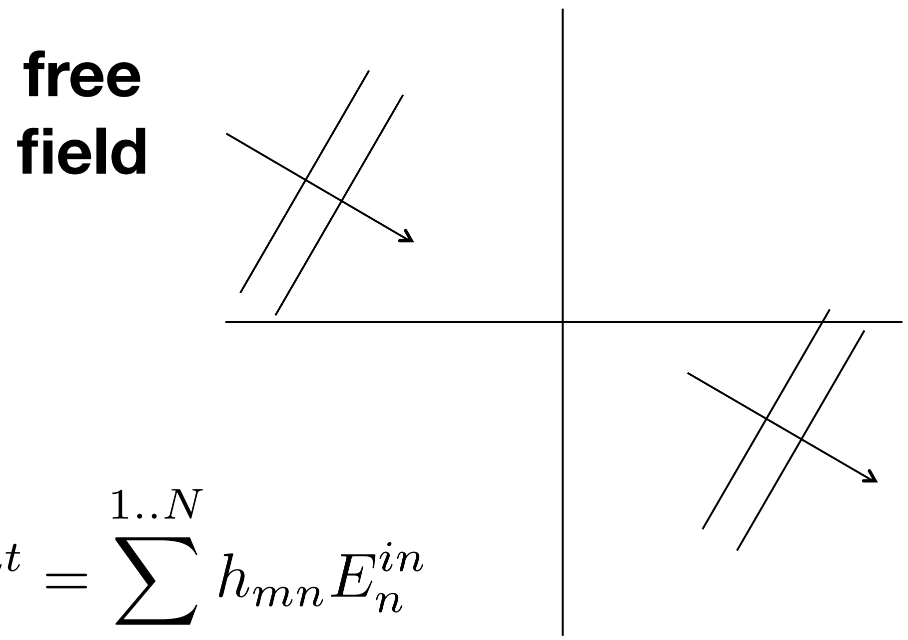

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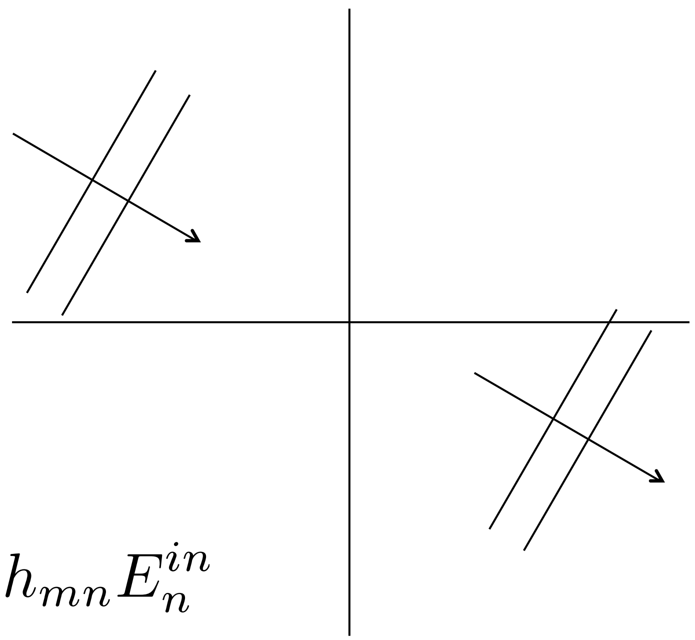
A more general approach : the transmission matrix

free field



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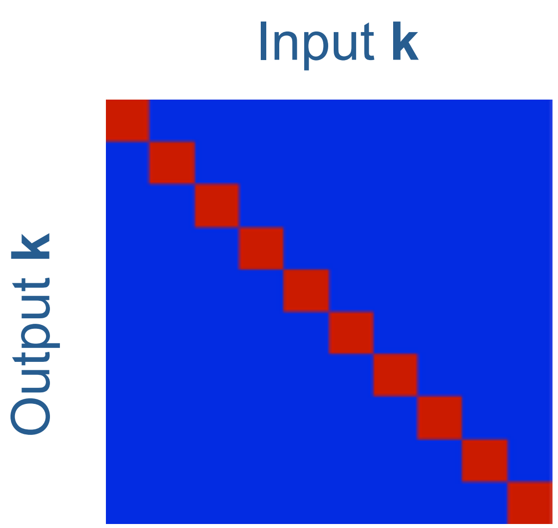
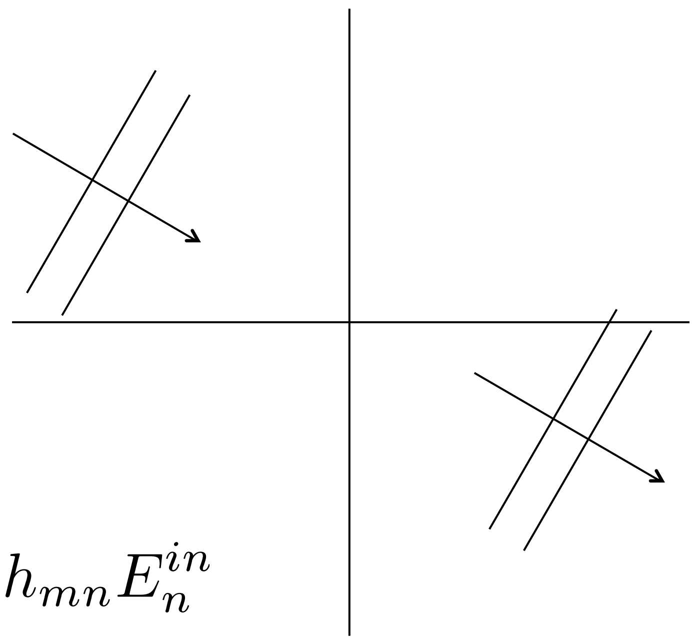
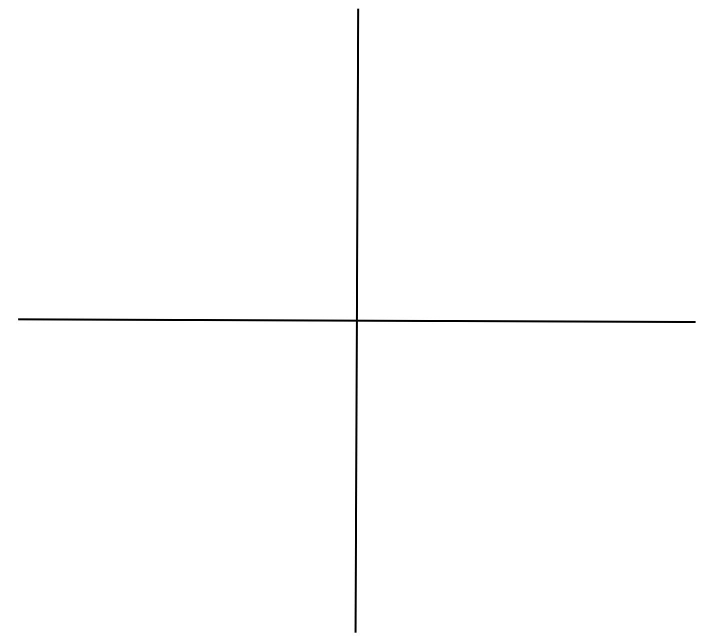


Identity Matrix

A more general approach : the transmission matrix

free field





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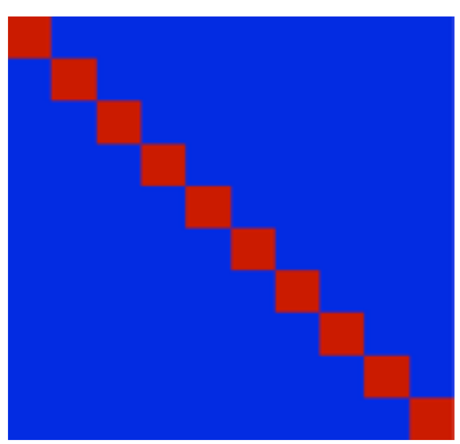

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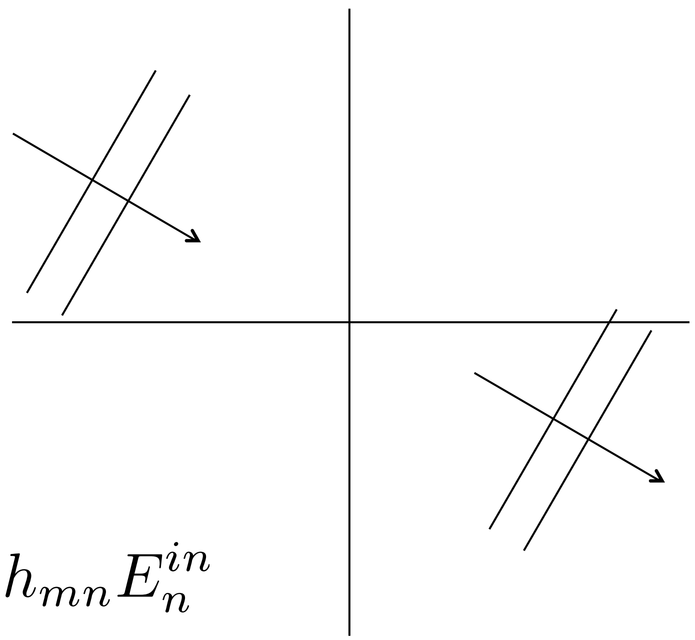

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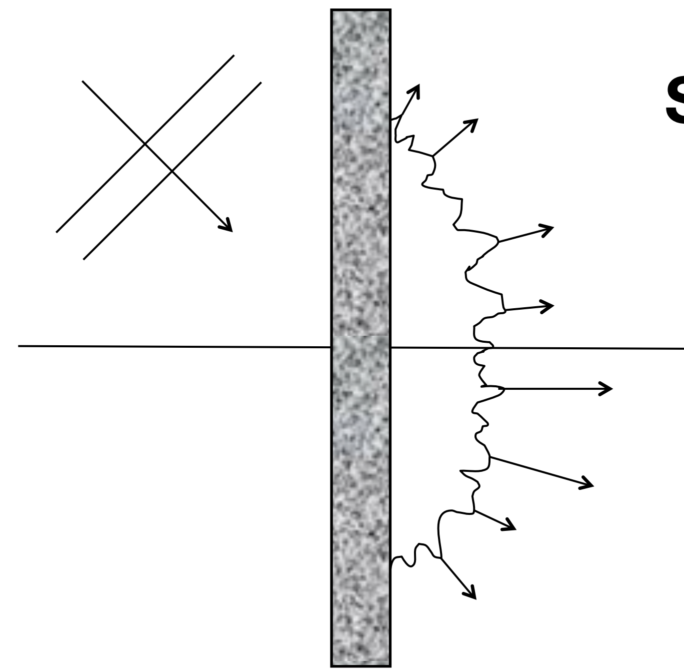
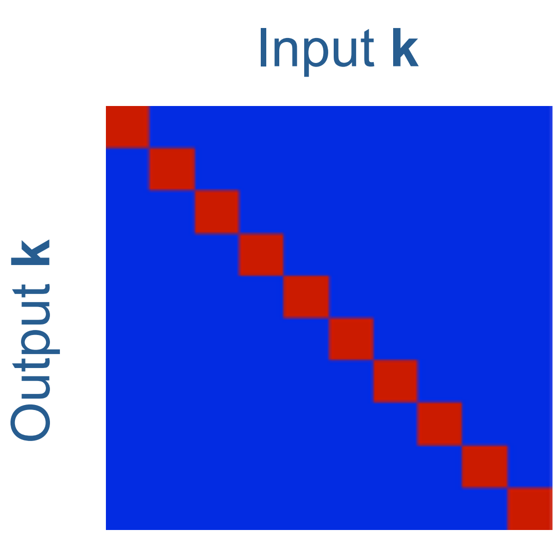


Scattering material



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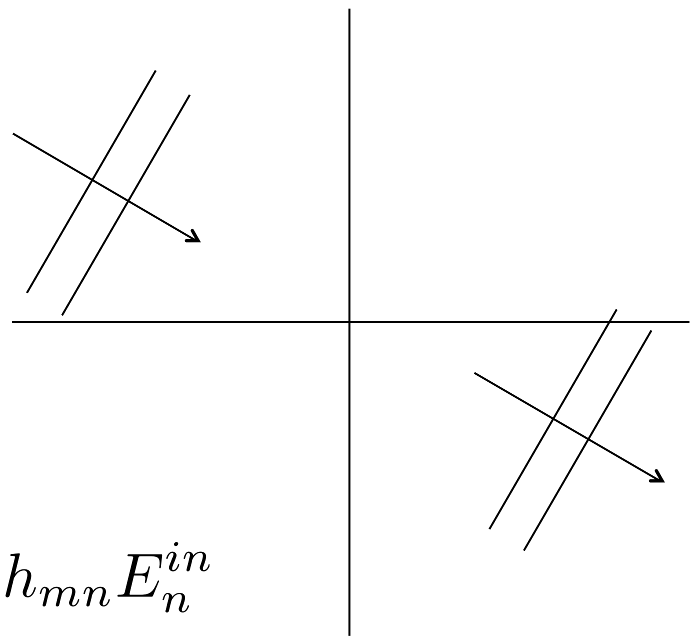

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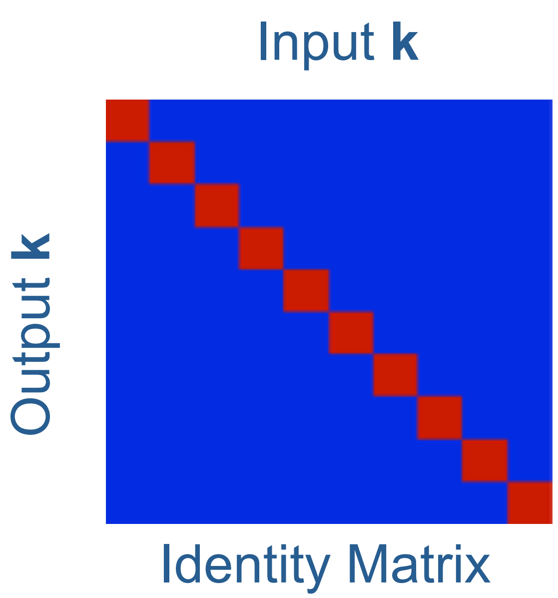

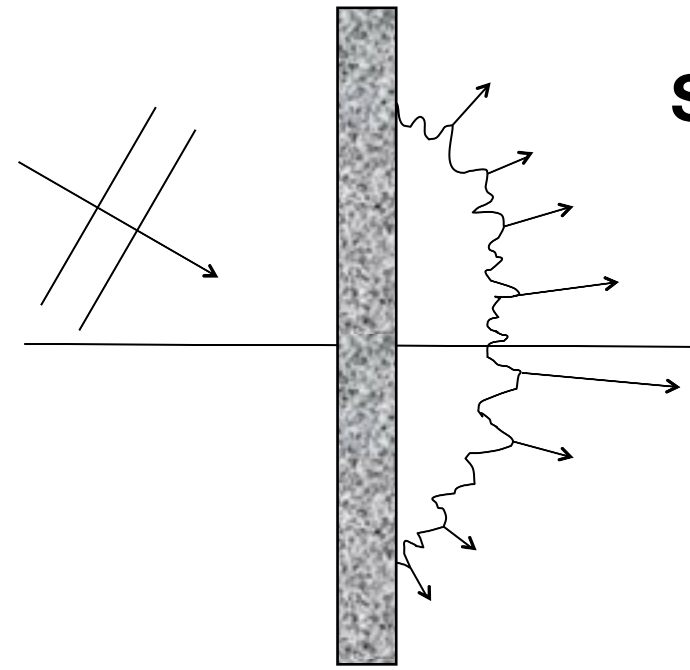

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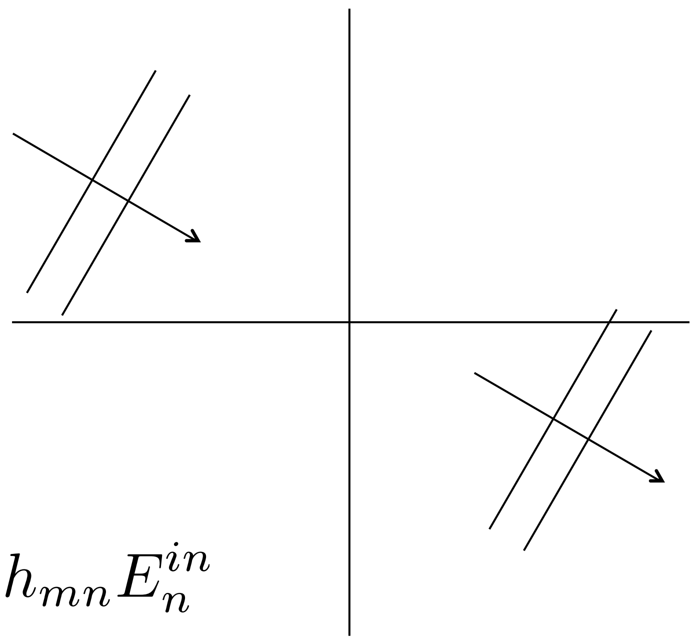

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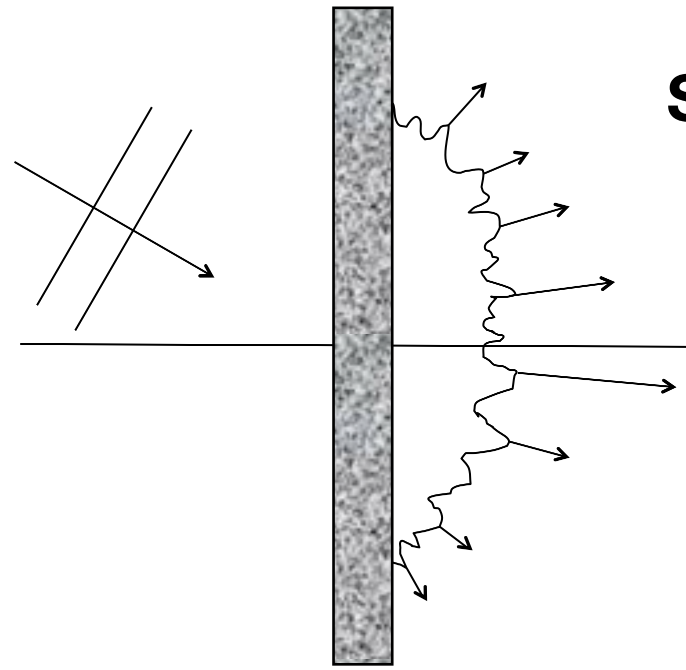
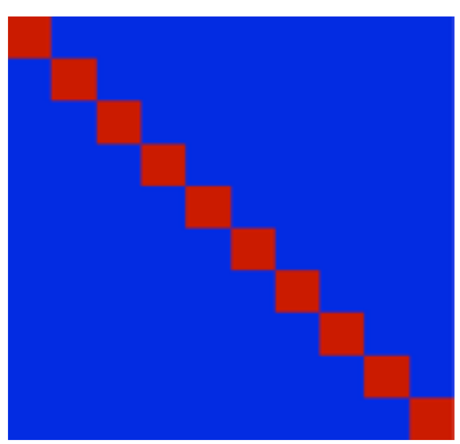


Input **k**

Output **k**



Identity Matrix

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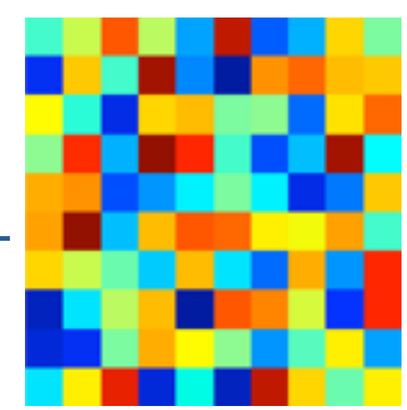
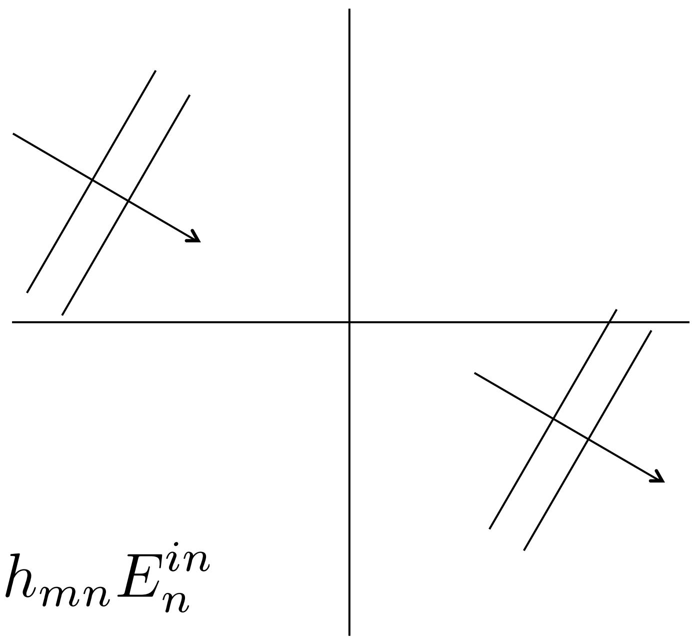
Output **k**



Seemingly Random Matrix

A more general approach : the transmission matrix

free field



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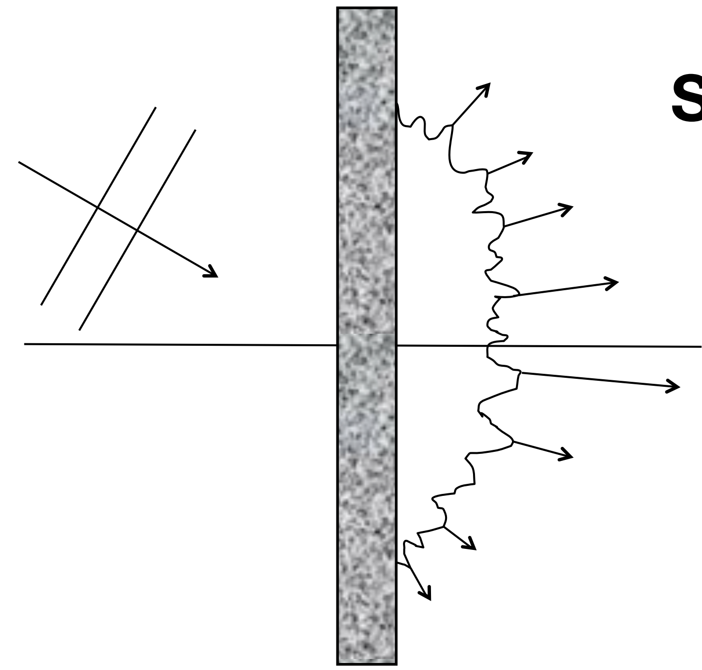
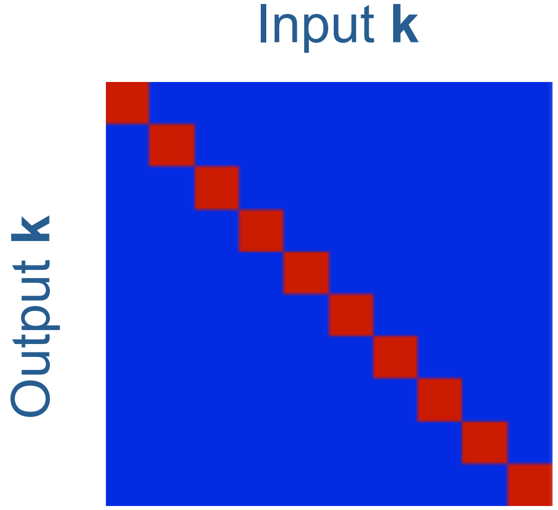
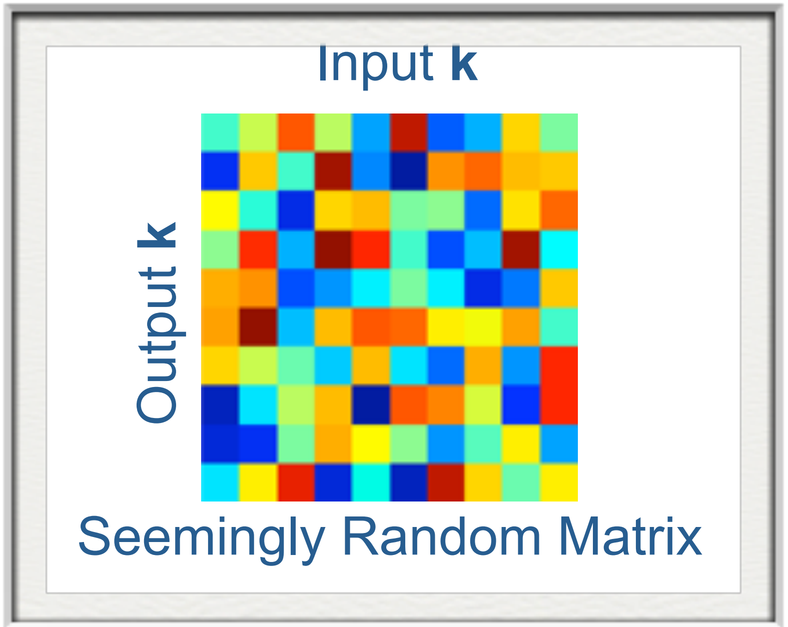


Scattering material



Identity Matrix



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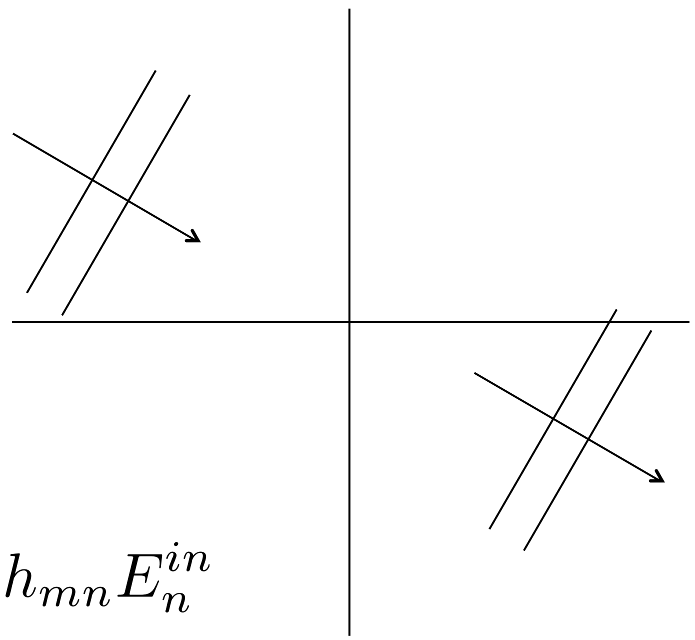
A more general approach : the transmission matrix



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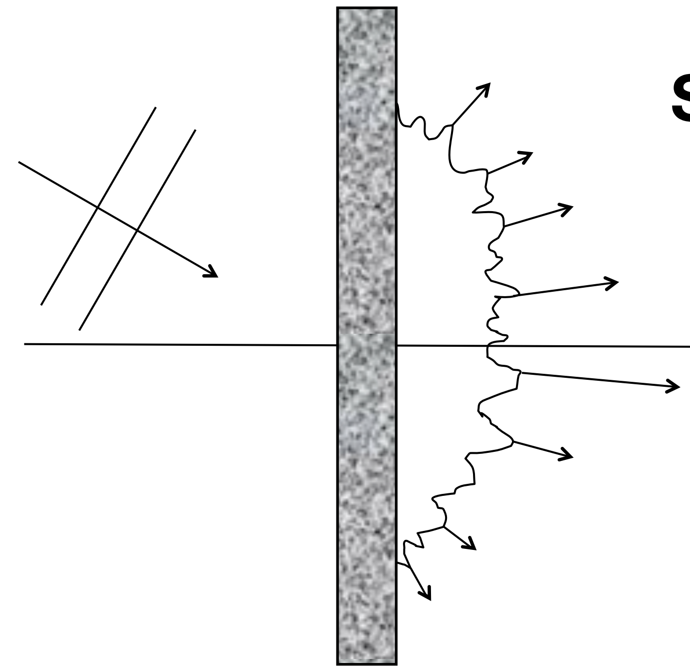
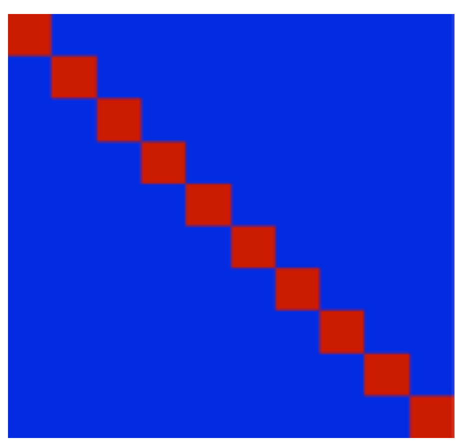
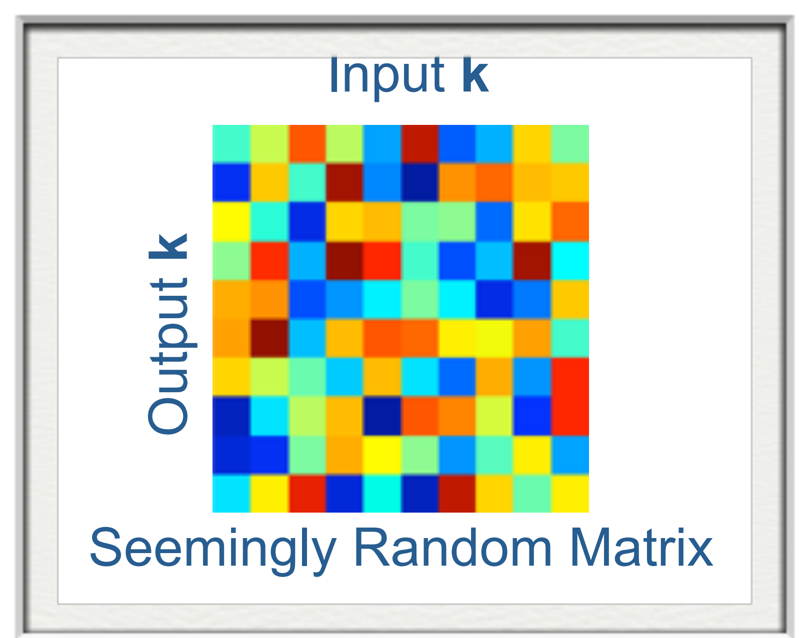
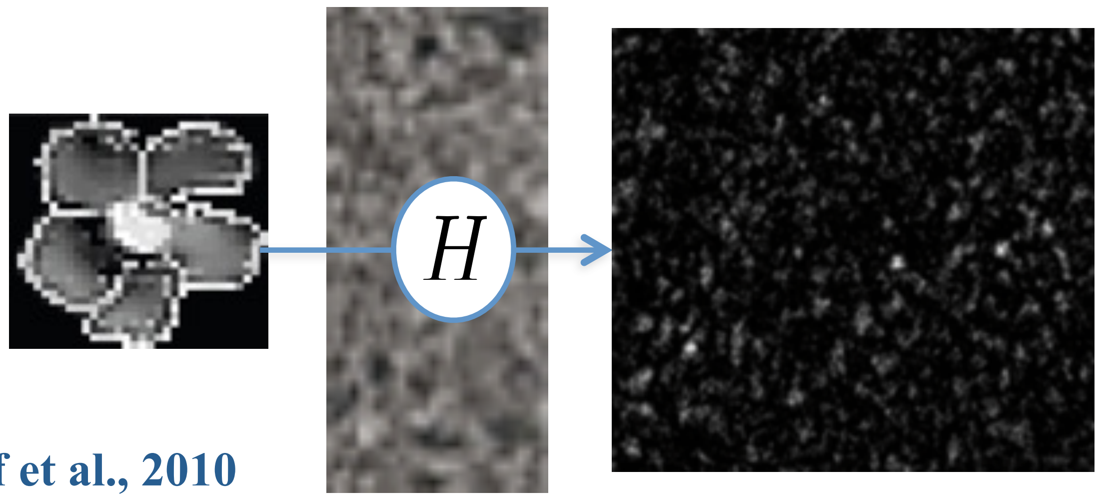






Gaussian iid measurements :
"optimal" for CS !

Exploiting H for imaging



Popoff et al., 2010

Linear Reconstruction

Tikhonov

$$(H^\dagger H + \sigma I)^{-1} H^\dagger$$

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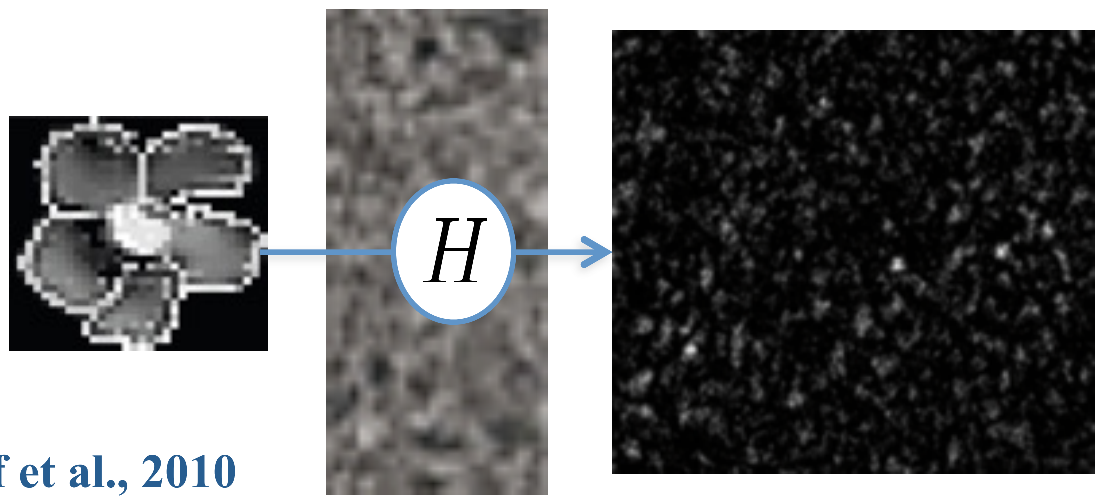
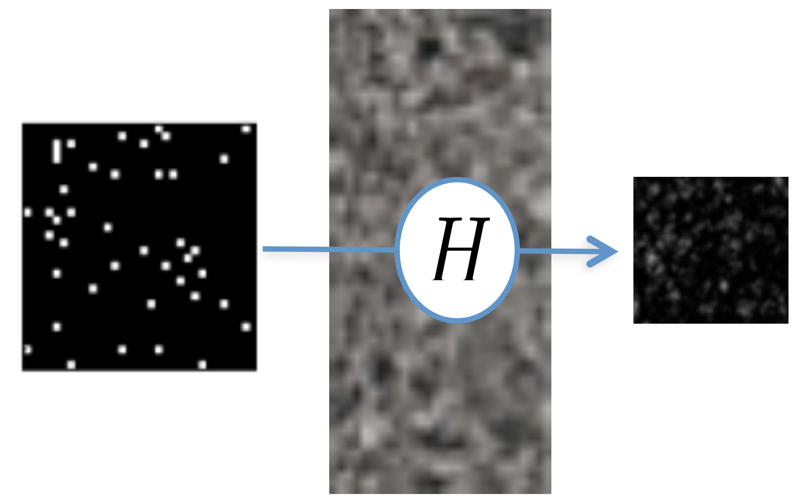


Popoff et al., 2010

Sparse image



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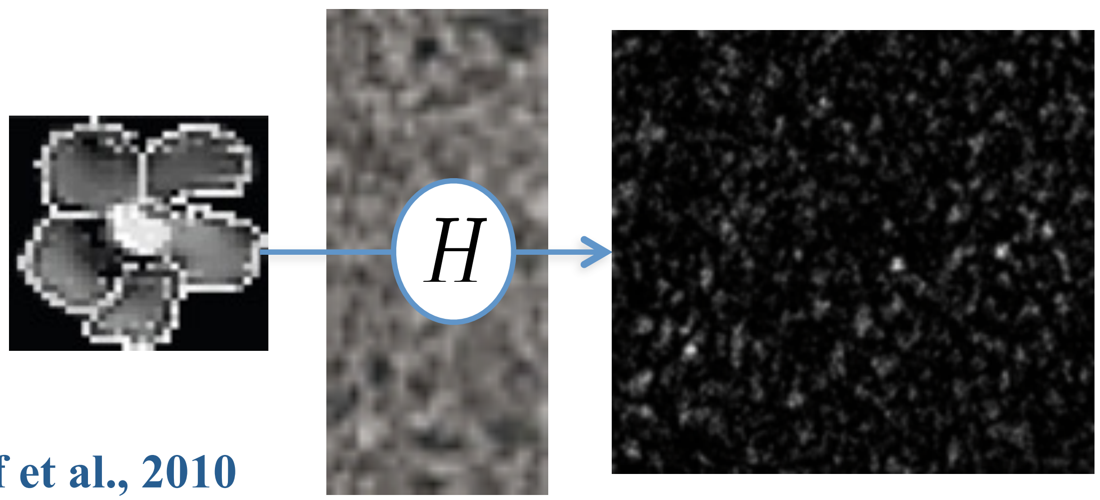
Non-linear Reconstruction

Sparse reconstruction (l1 or l0)

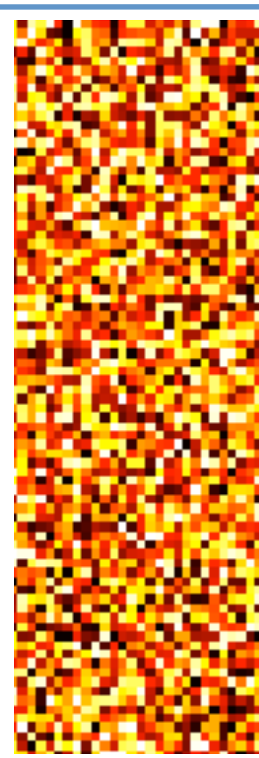
$$u = \arg\min_{u} ||x - H\, u||_2^2 + \lambda\|u\|_{1}$$

Exploiting H for imaging



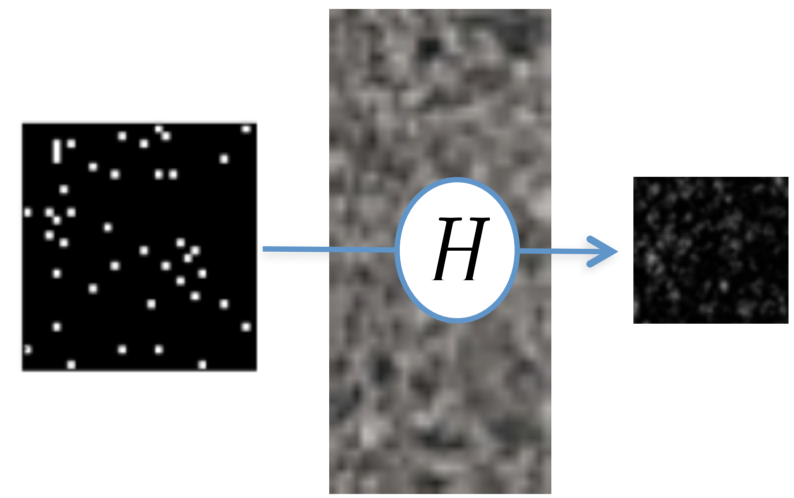
Popoff et al., 2010

Linear Reconstruction

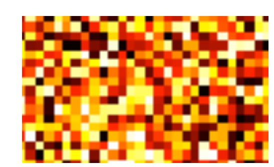
H 

At least as many measurement pixels as input pixels

Sparse image

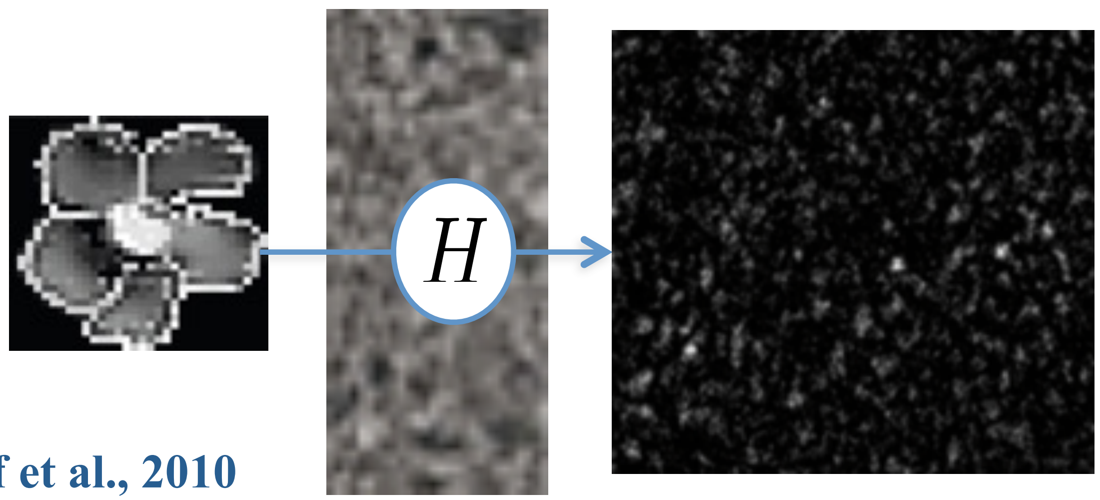


Non-linear Reconstruction

H 

Number of measurement pixels driven by sparsity (<< input pixels)

Exploiting H for imaging



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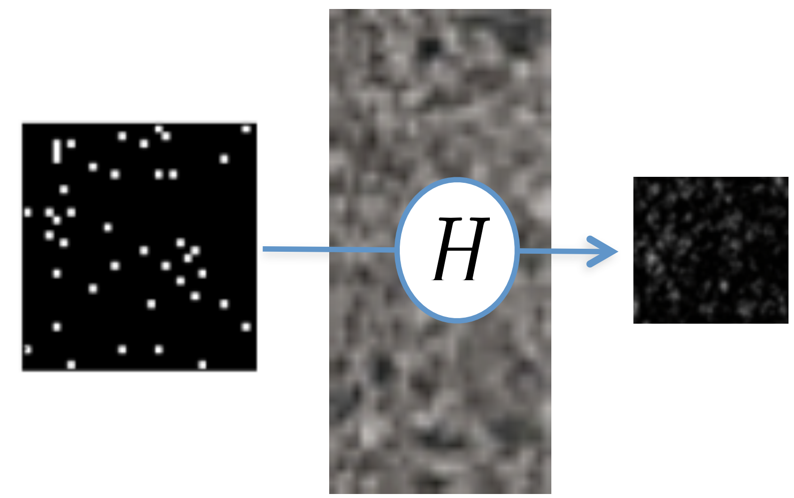

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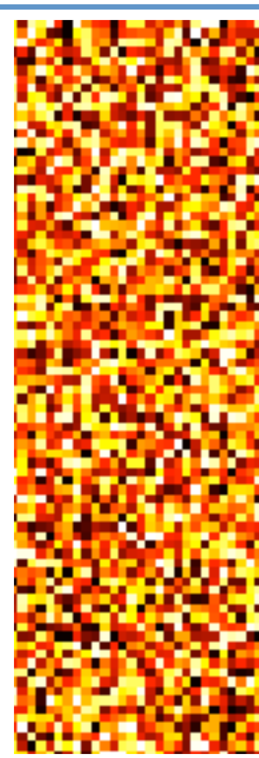

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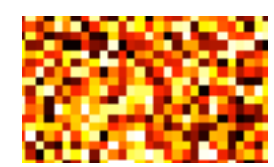

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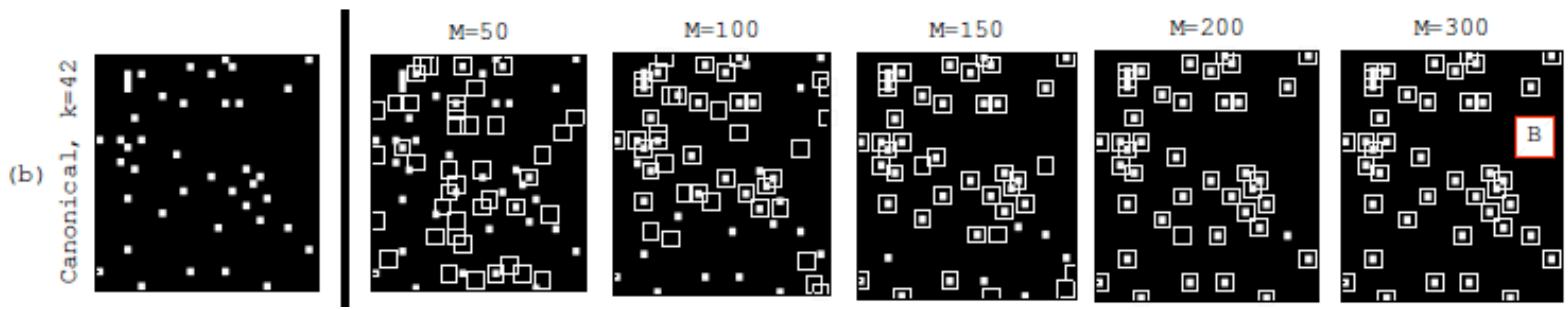
Compressive imaging with scattering media

original image
1024 pixels

number of pixels M used for reconstruction



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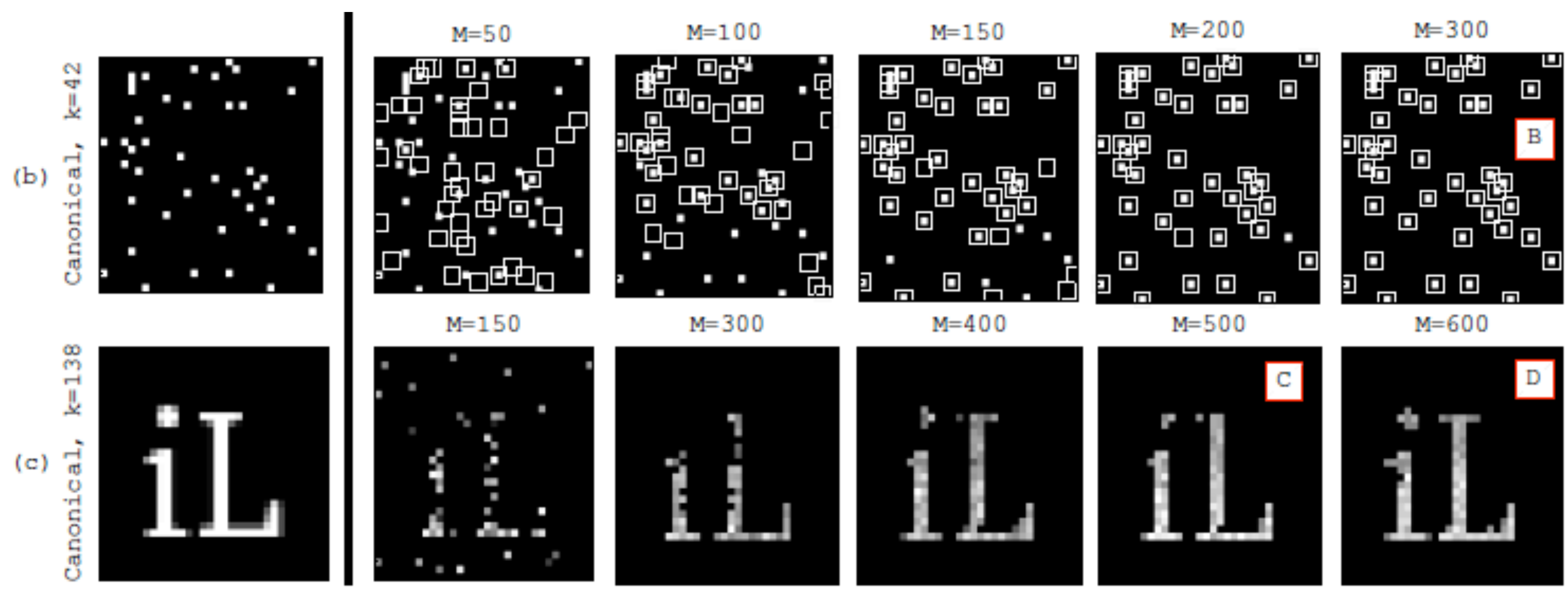

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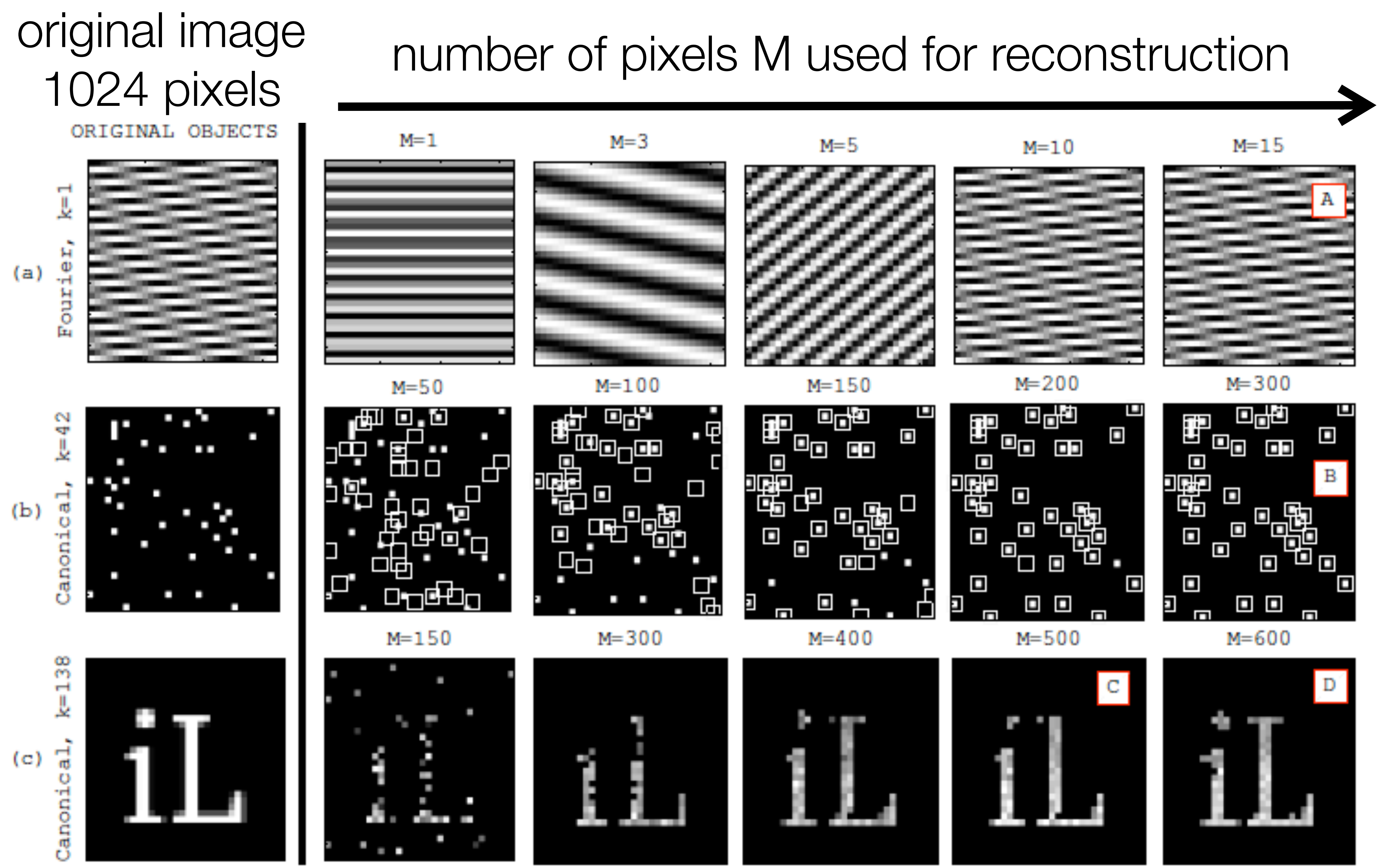

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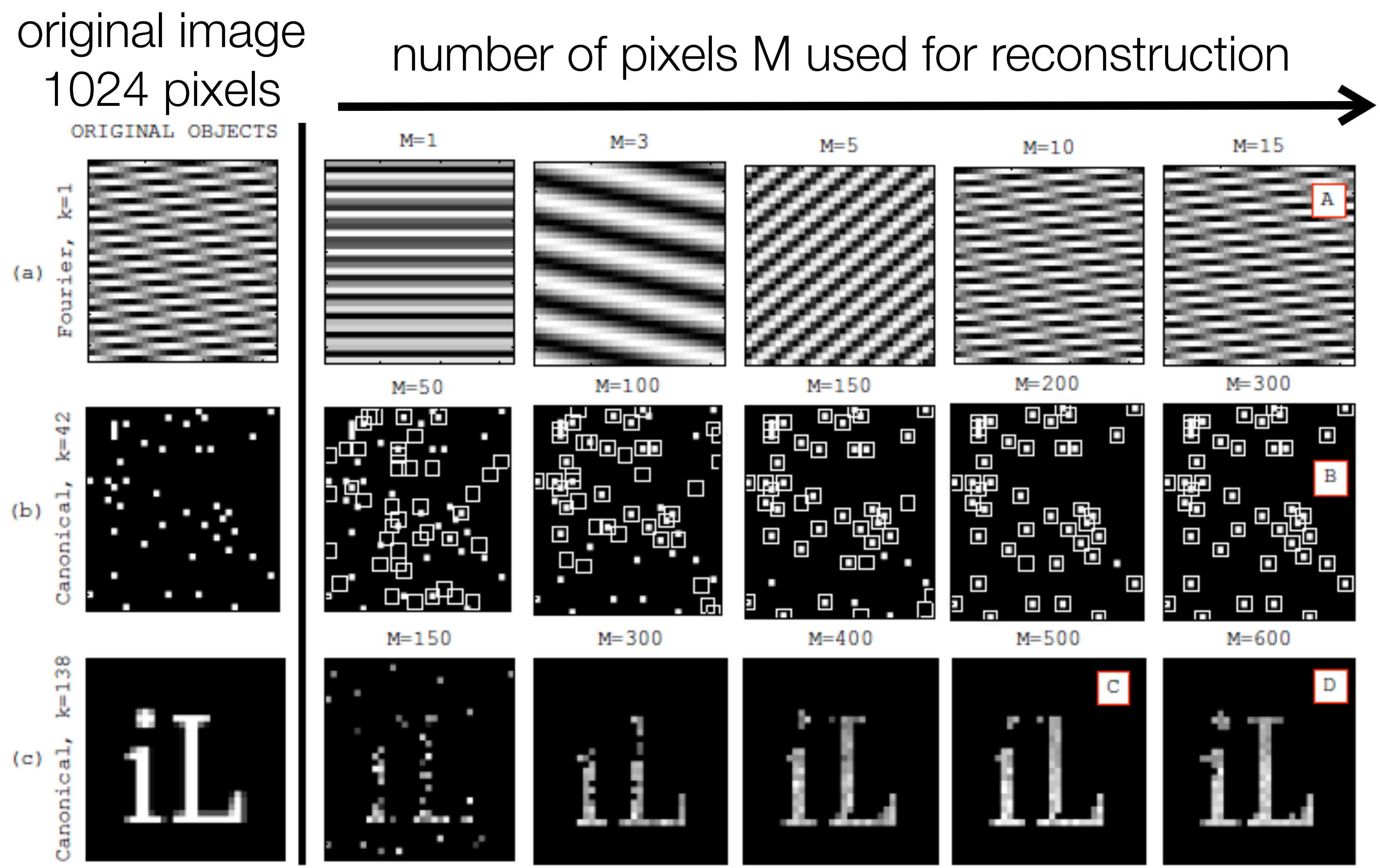
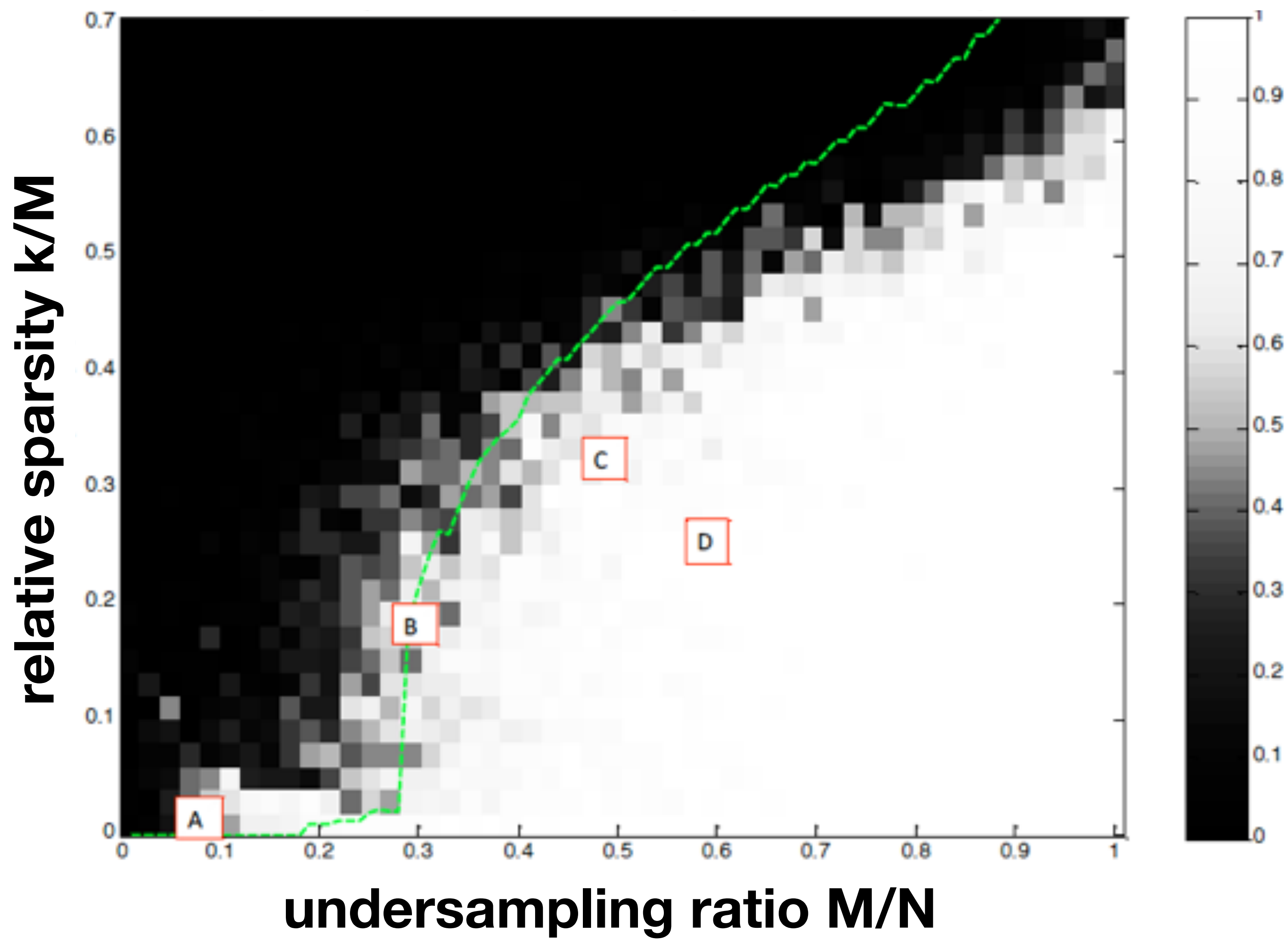


Each pixel provides information about the whole image

Compressive imaging with scattering media

Probability of success for recovery (MMV with 3 observations)



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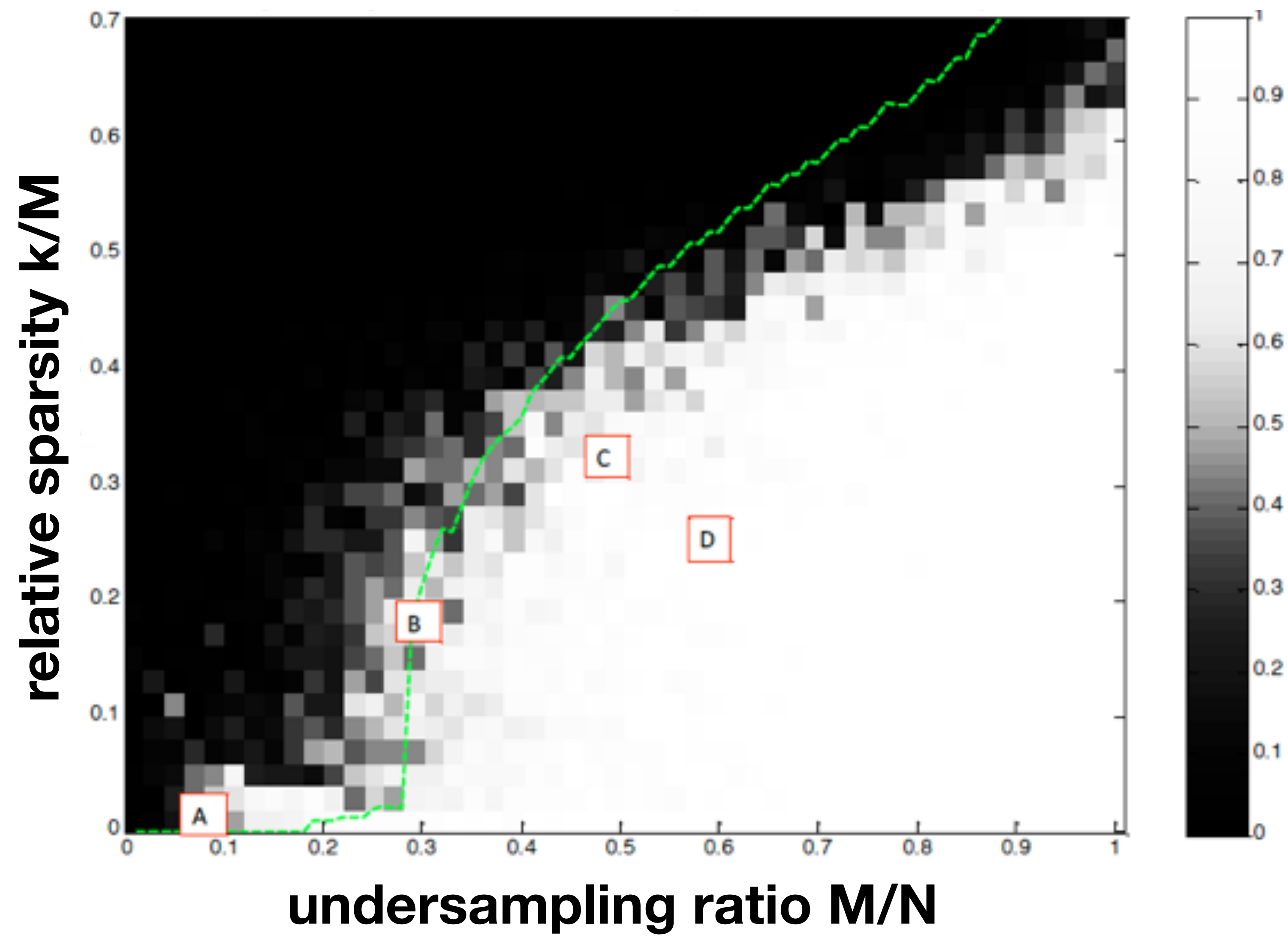

about 10^5 experiments needed !
(measurements are fast ! medium is stable only for ~ 30 min)

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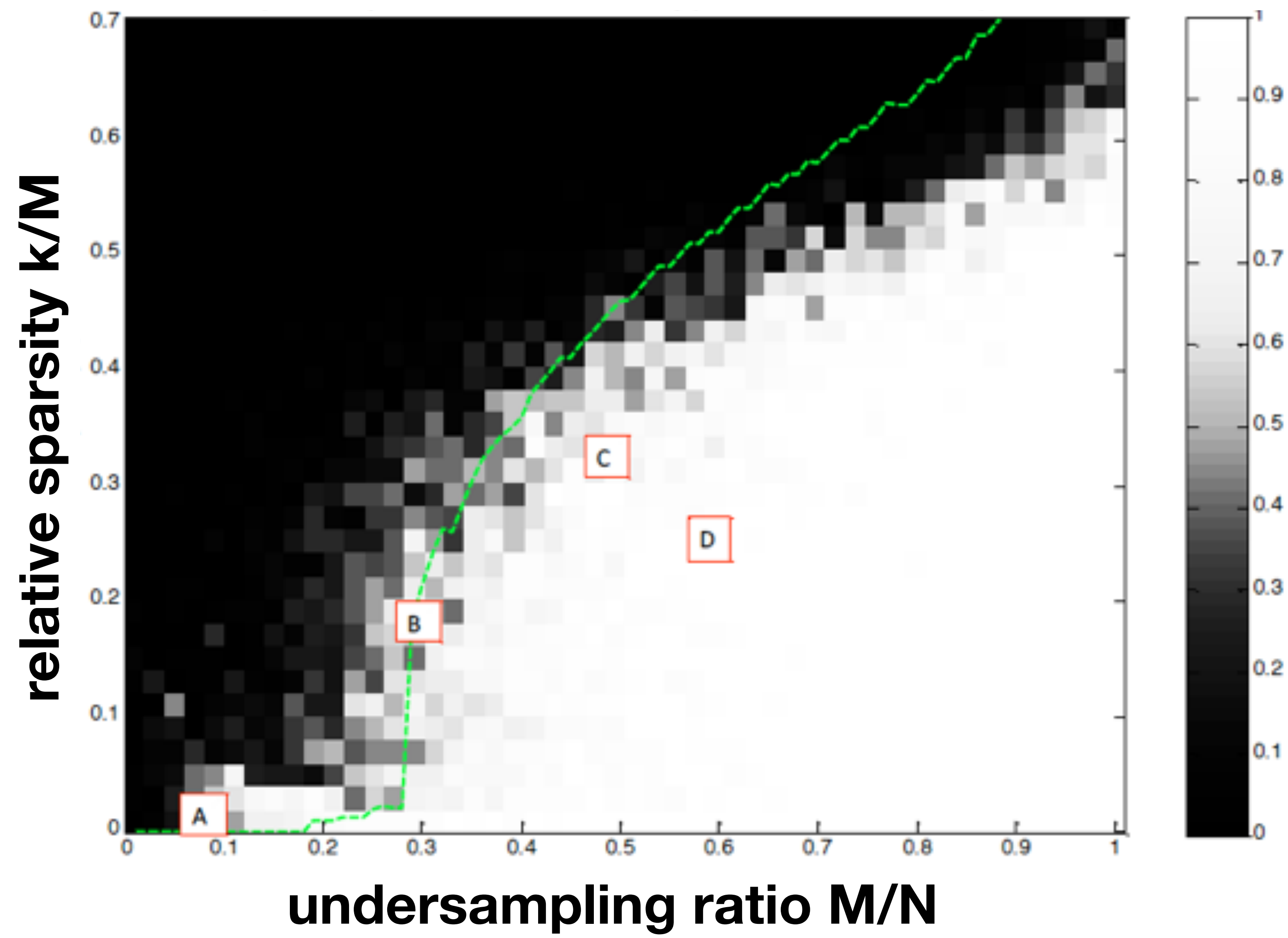

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Why is it different from the standard «*a la* Donoho-Tanner» phase transition ?

Compressive imaging with scattering media

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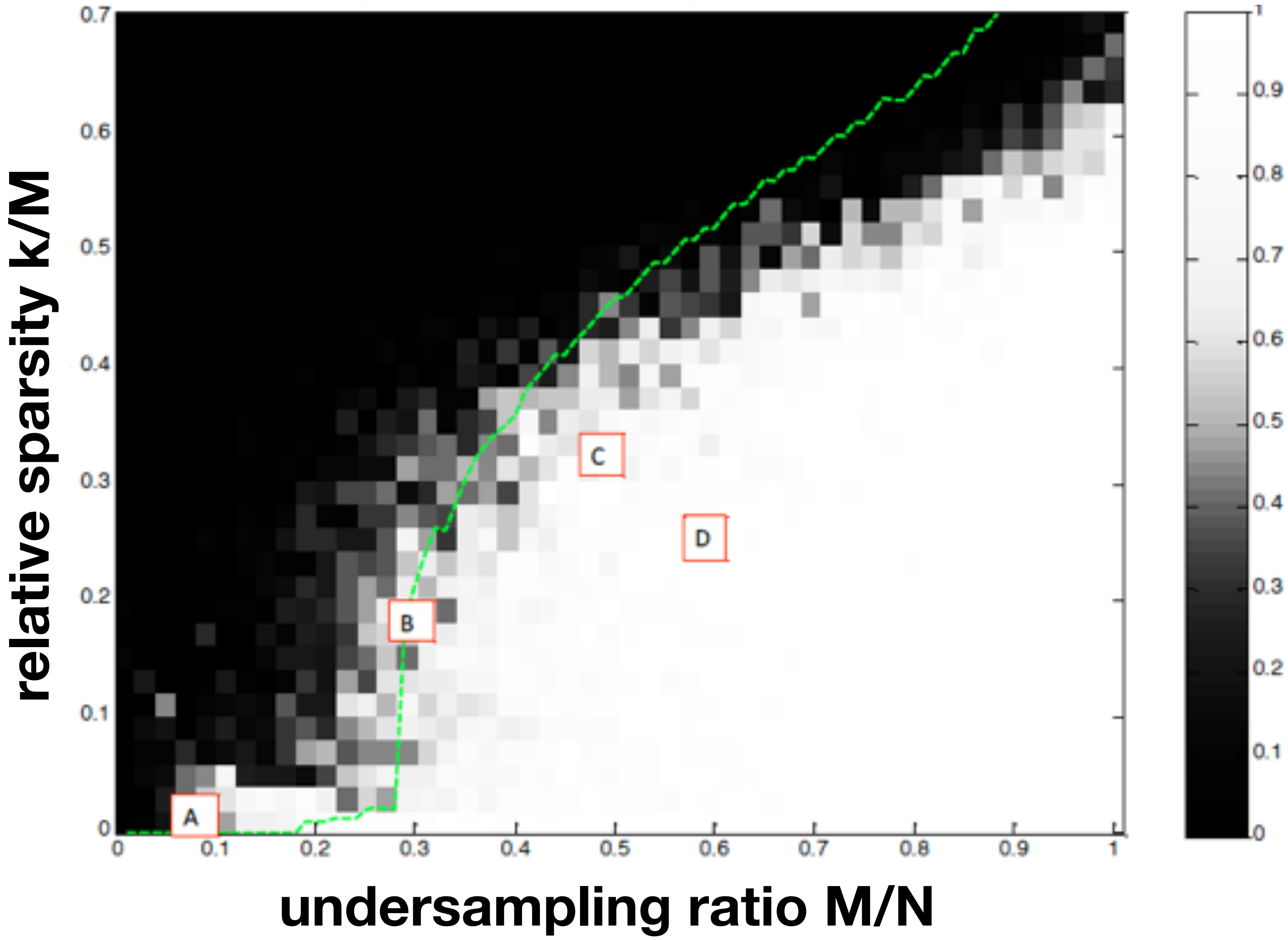

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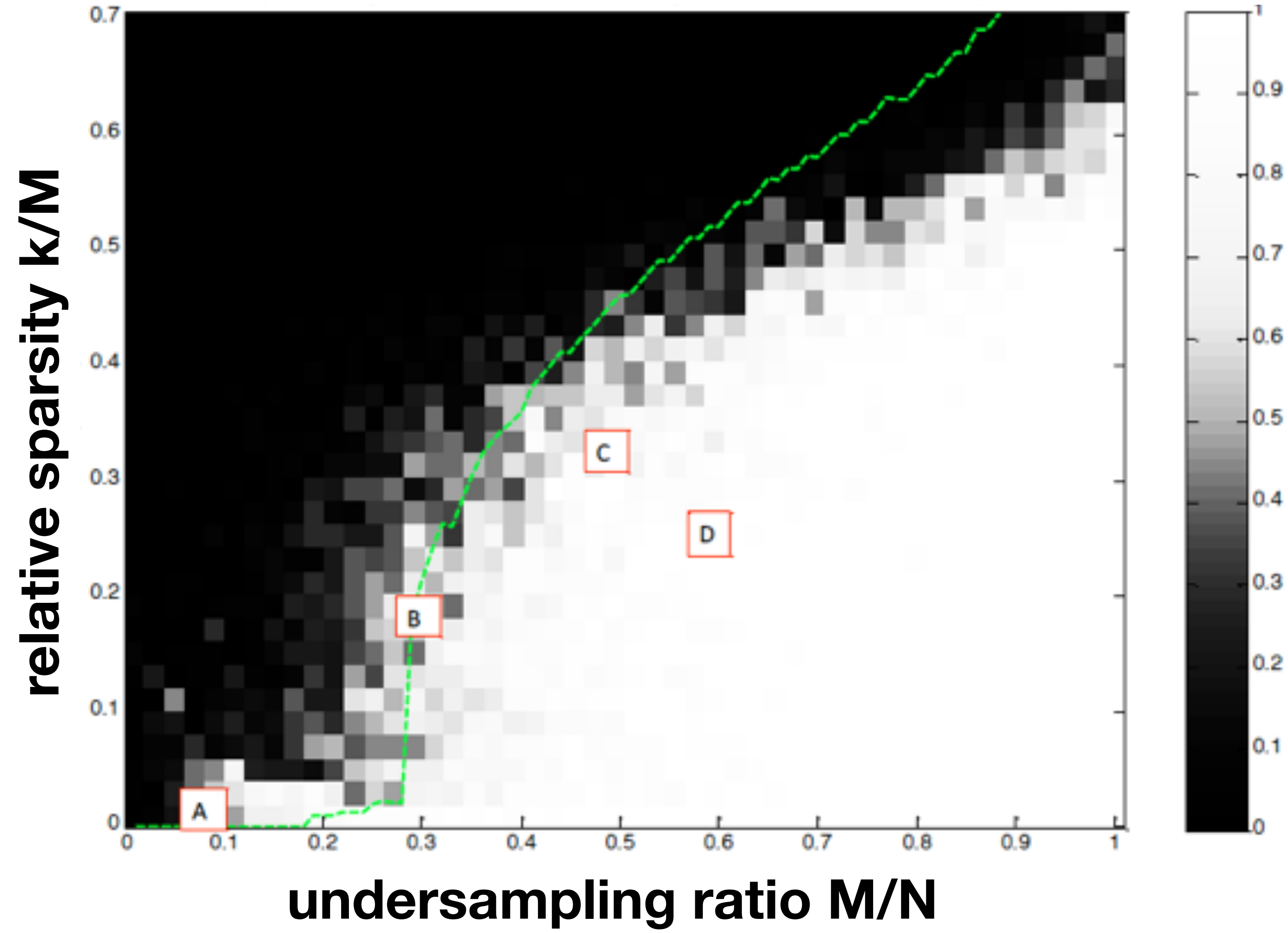

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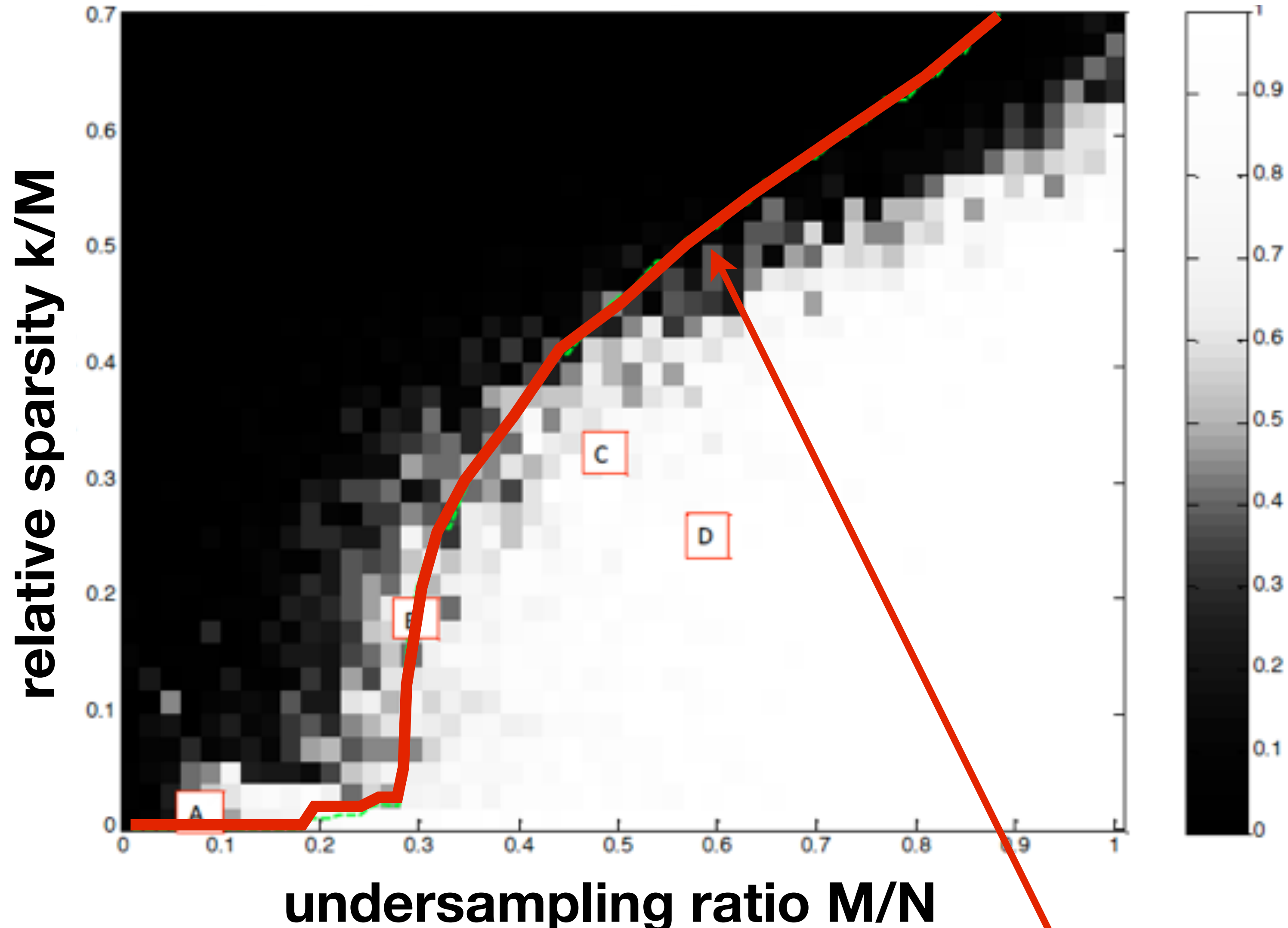
- algorithm used is SOMP (group-l_0), not a l_1 minimizer
- noise in the measurement *and* in the calibration (estimation of H)

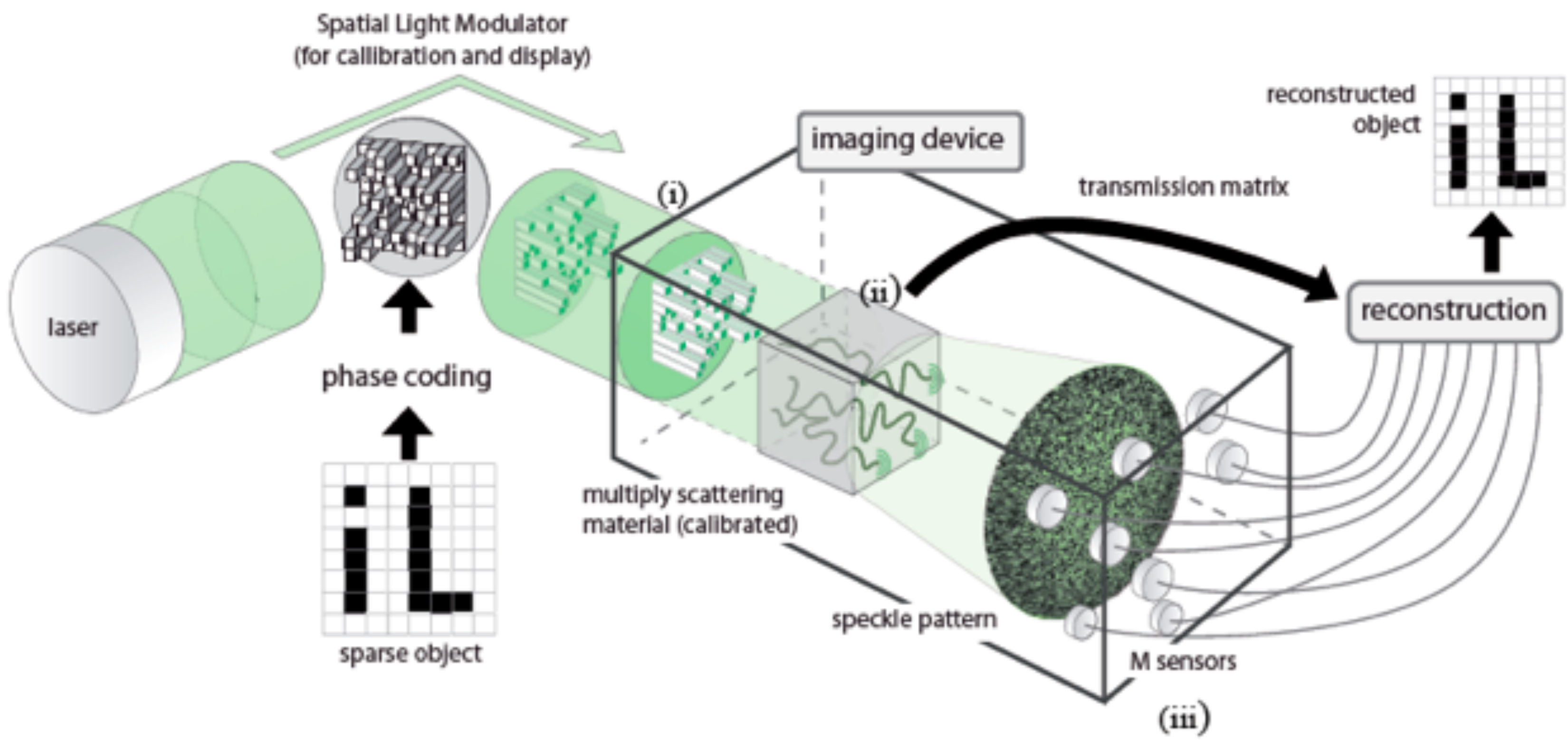
Compressive imaging with scattering media

Probability of success for recovery (MMV with 3 observations)



Transition curve obtained by numerical simulation with y = M x + e
with M and e with gaussian iid entries
variance of e = 3% of variance of M
same procedure : error added at calibration and measurement

Compressive imaging with scattering media



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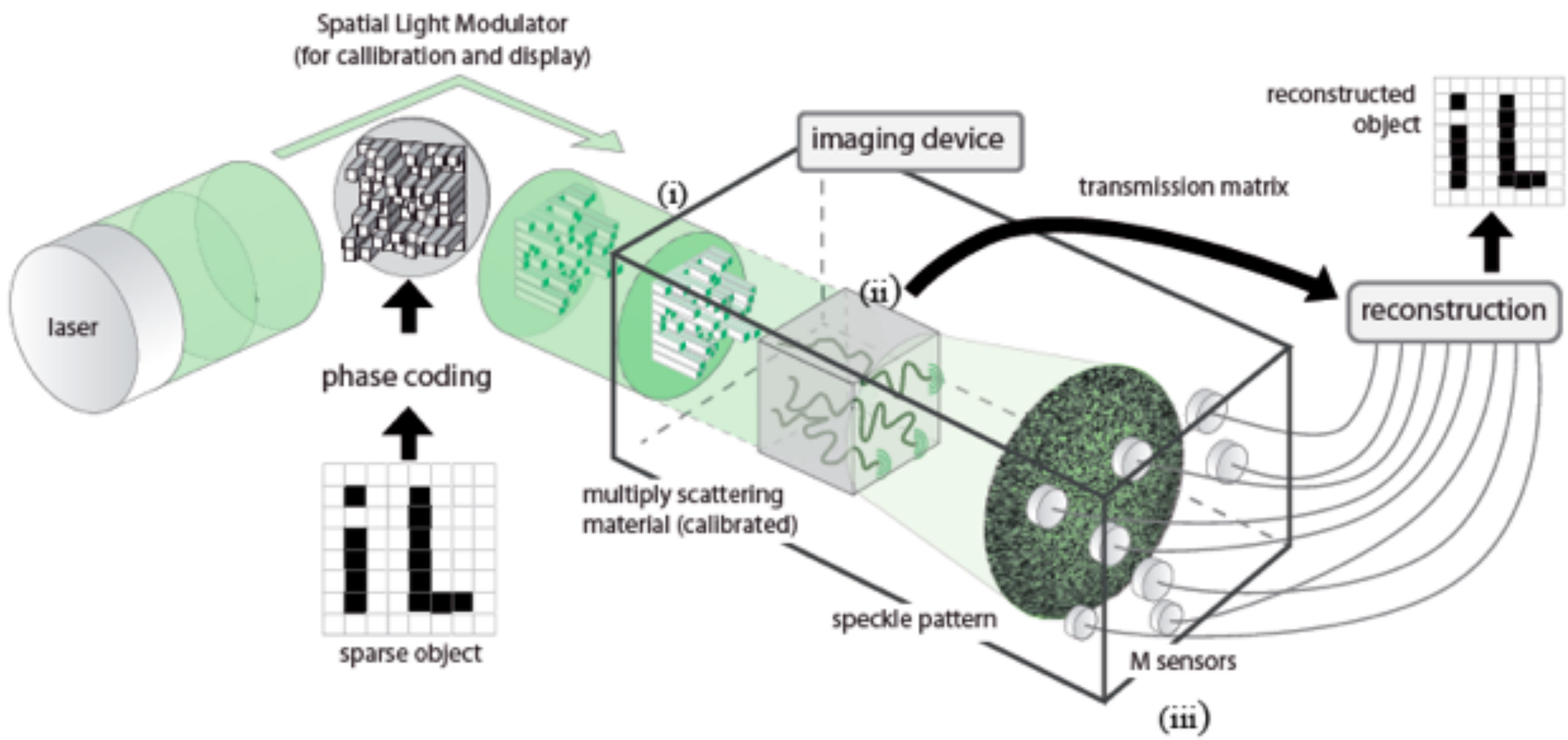

Liutkus *et al.*,
Scientific reports (4)
(2014)

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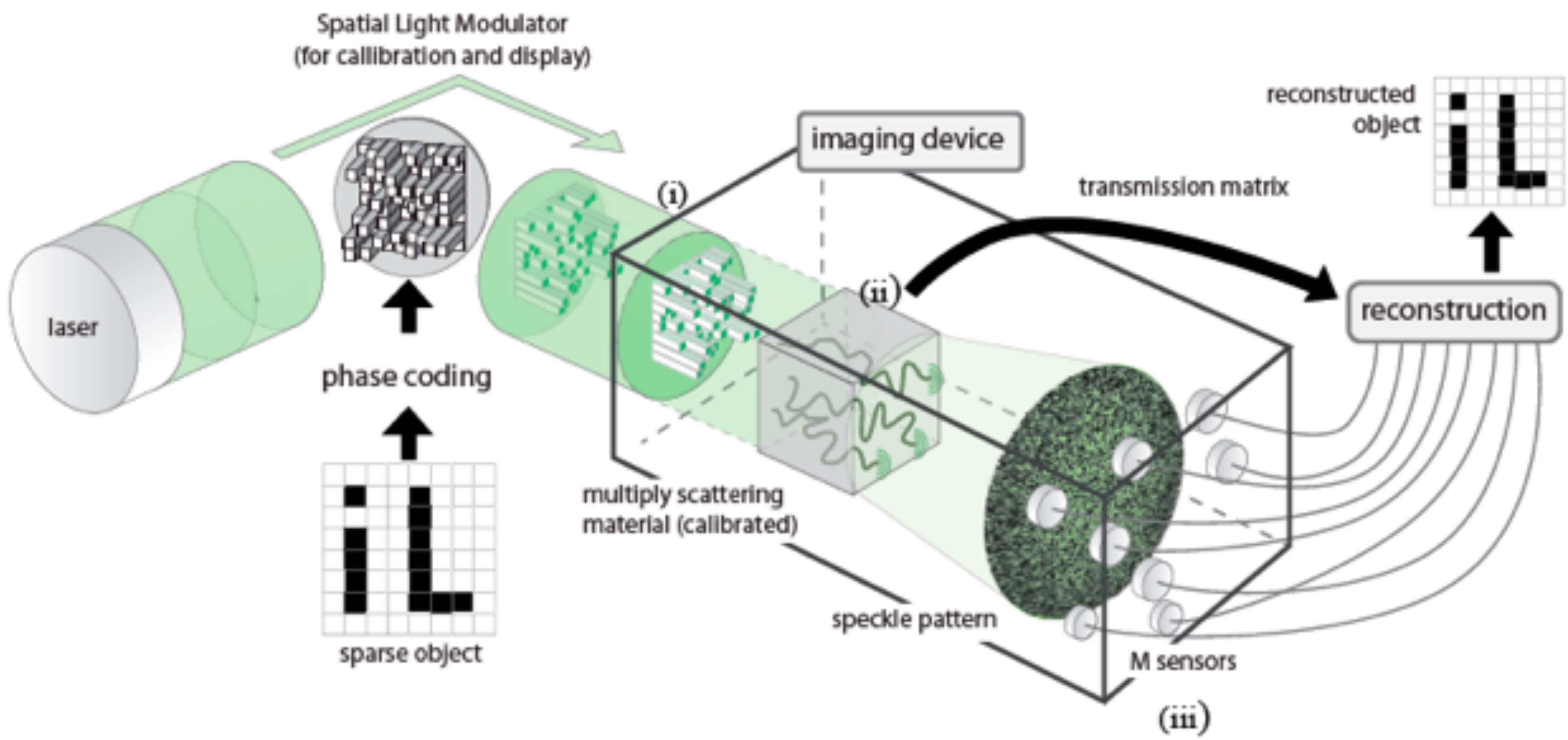

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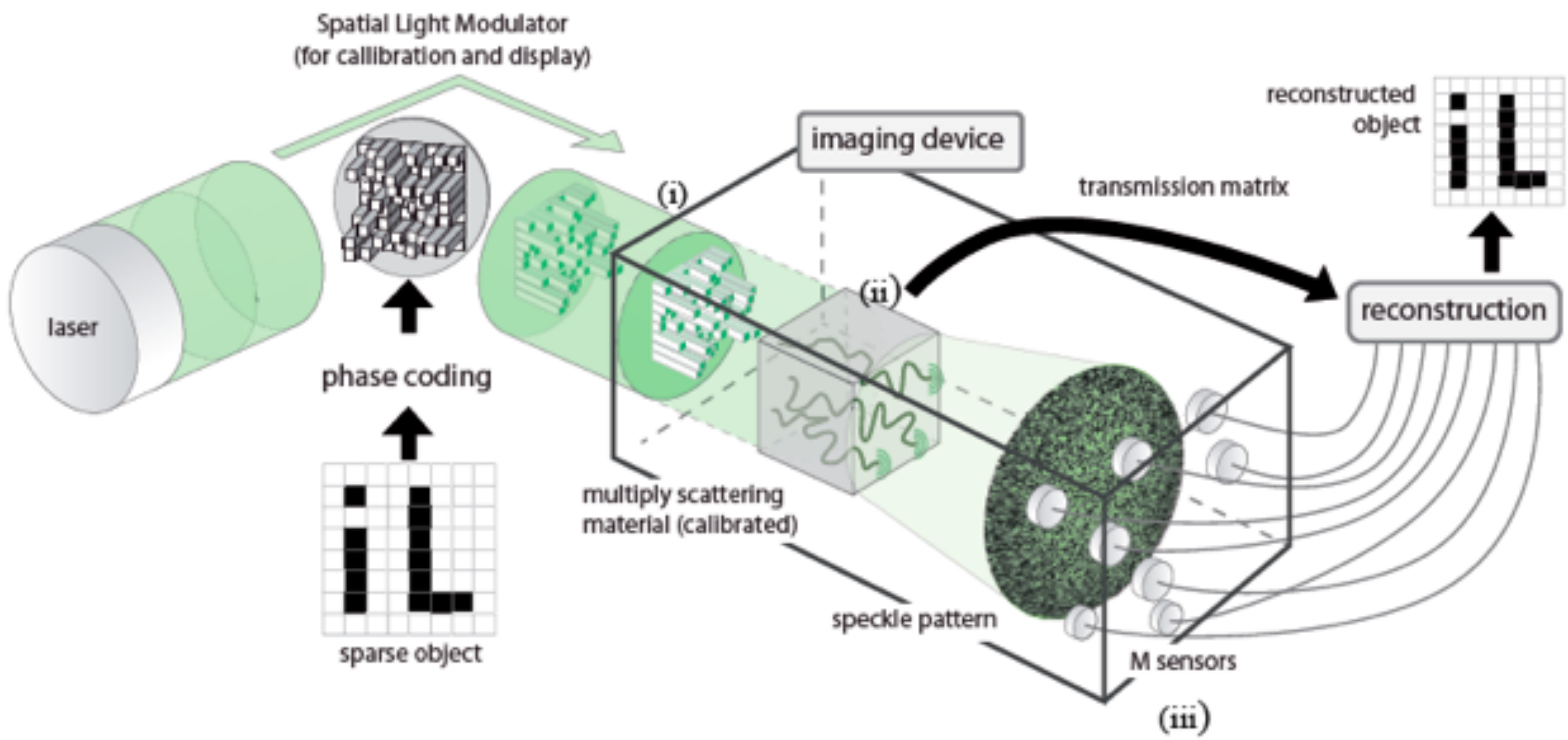

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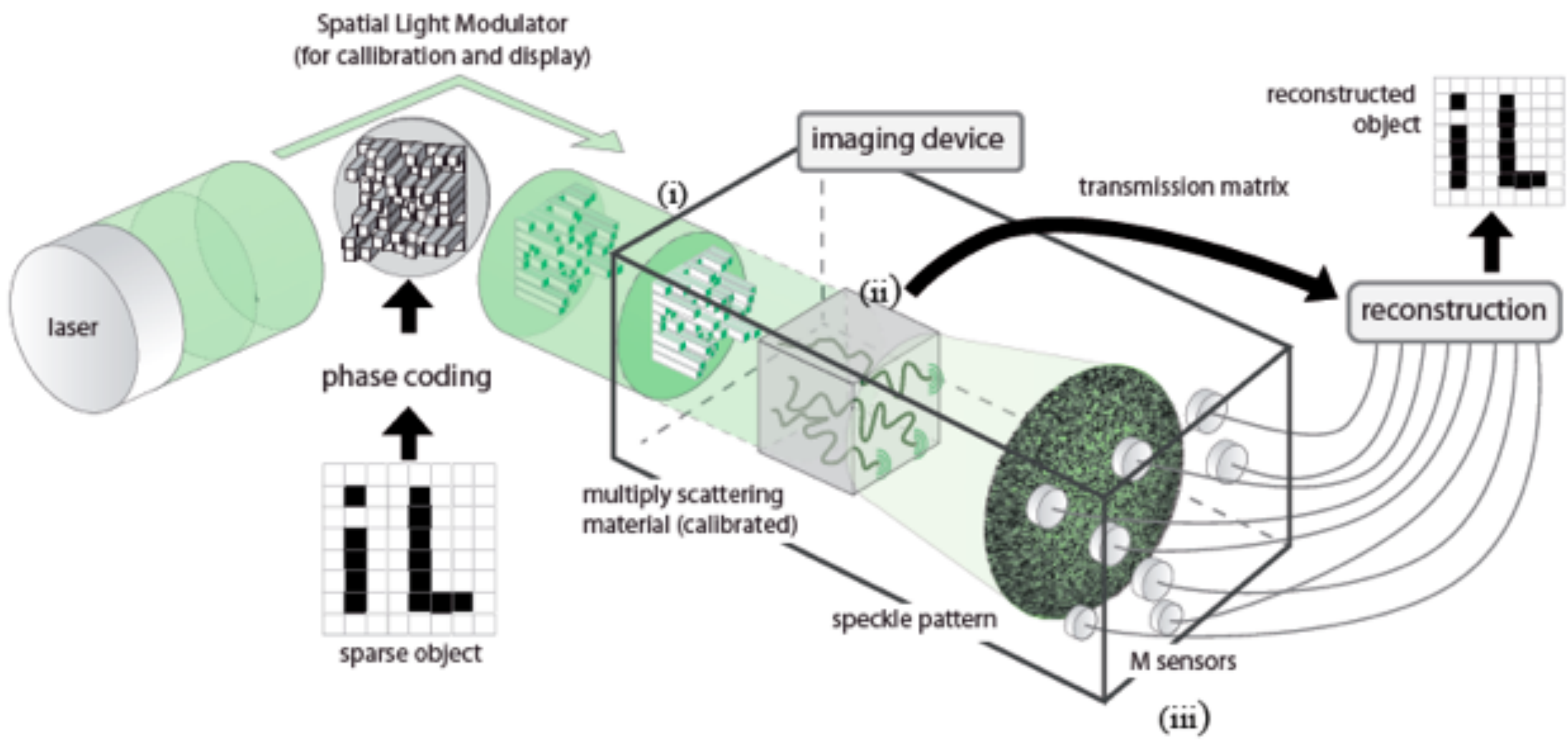

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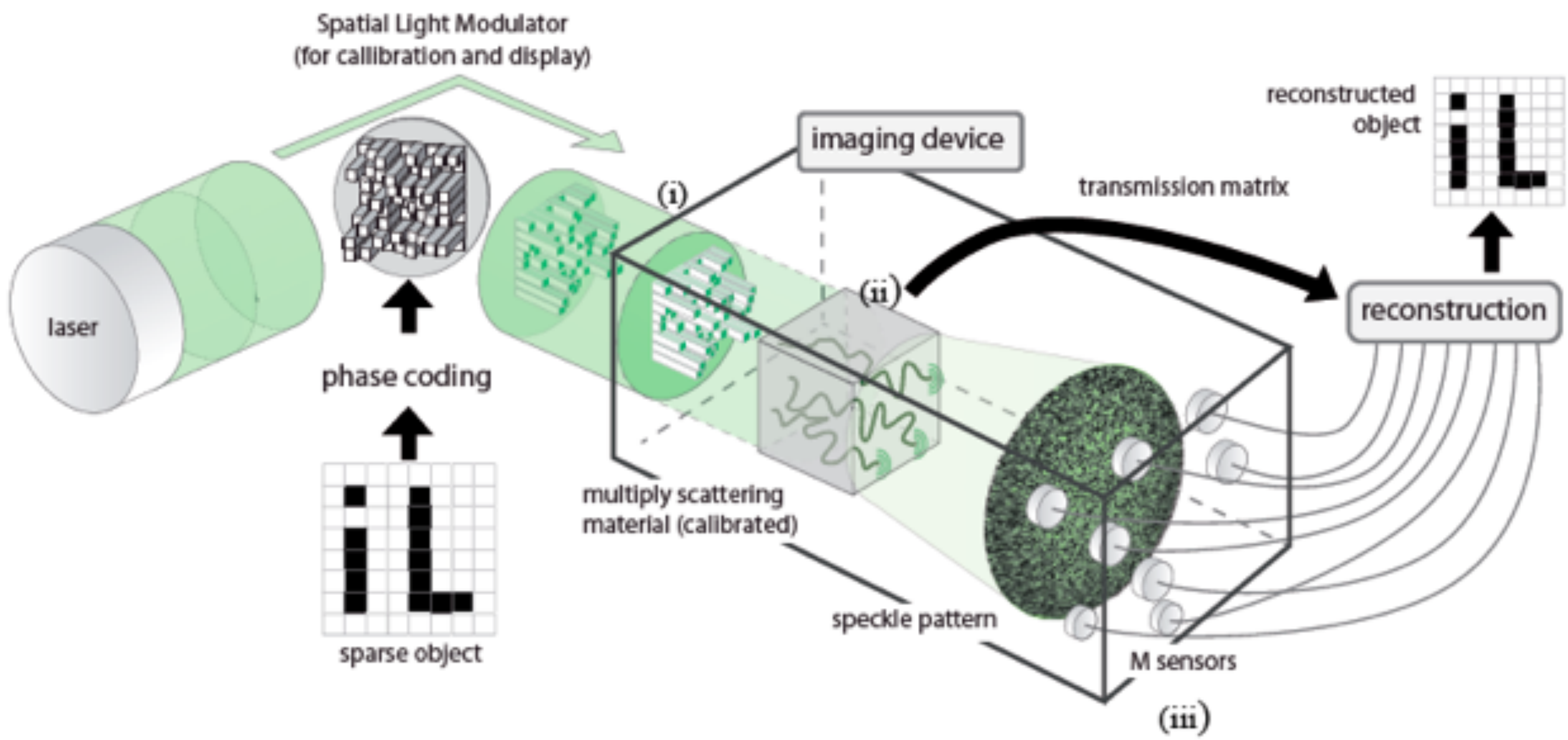

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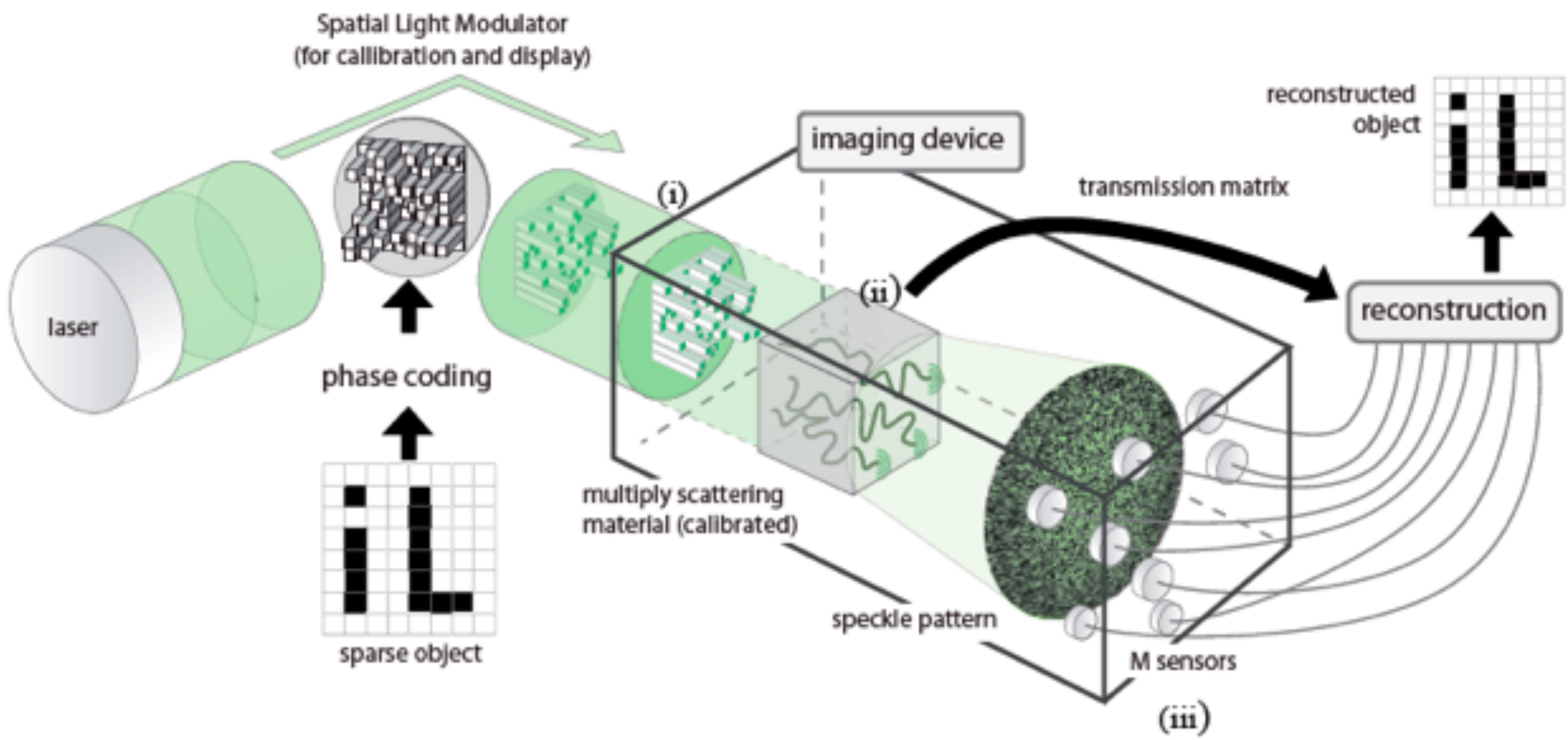

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- From *imaging through scattering media* (challenge)
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- Randomness helps ! “optimal” scrambling of information
- Trade hardware for calibration
- A deep connection between *sensing* and *sampling*

Compressively Sensing acoustic fields

- Compressed sensing is a way to put prior information about the signal at the acquisition stage (sparse regularization) and a way to design corresponding efficient measurements

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