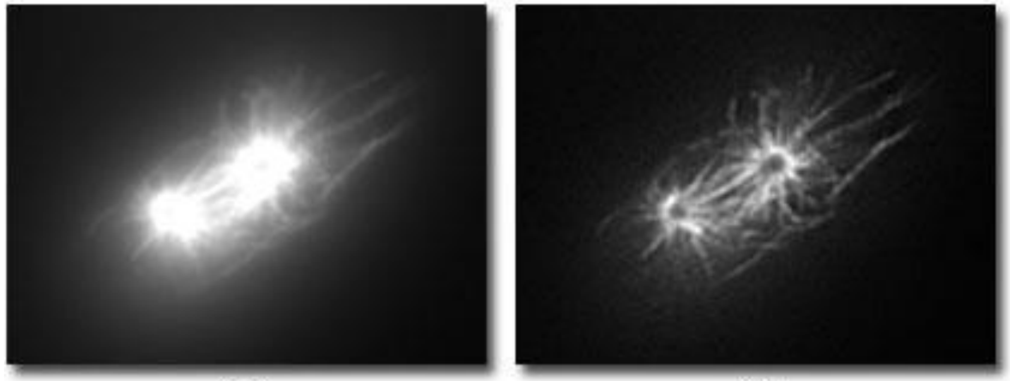
Dekonvolúció

3D Mikroszkópia és Dekonvolúció

Iterációs eljárások

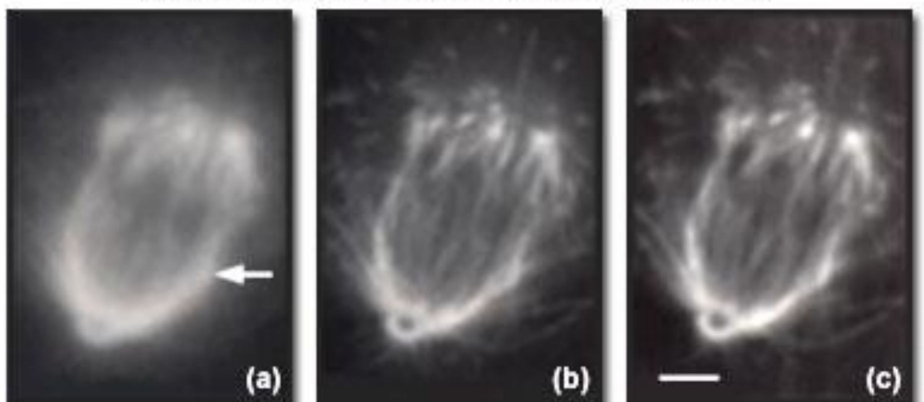
Before and After Nearest Neighbor Deconvolution Analysis



(a) (b)

Figure 1

Deblurring and Restoration Techniques

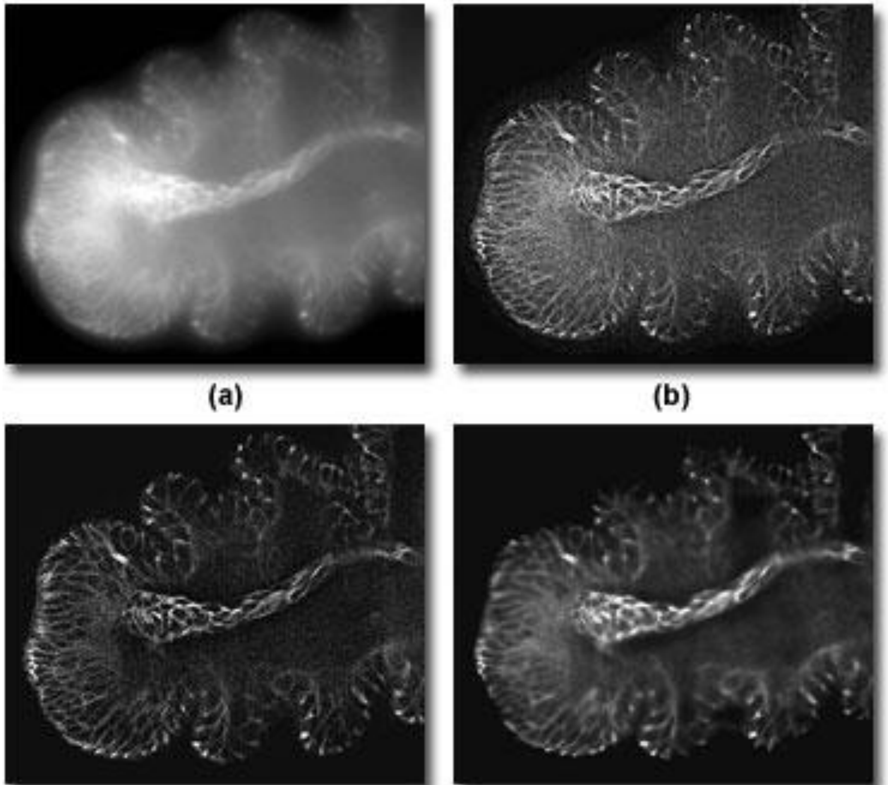


Original Data · Nearest Neighbor · Restored

Figure 2

3D image restoration or reconstruction using a Fast Nearest Neighbor deconvolution algorithm. The parameter dialog box requires the source image file name, the point spread function (PSF) image file name. Because this algorithm uses information from the nearest image layers, it deconvolves much faster than the Maximum Entropy method.

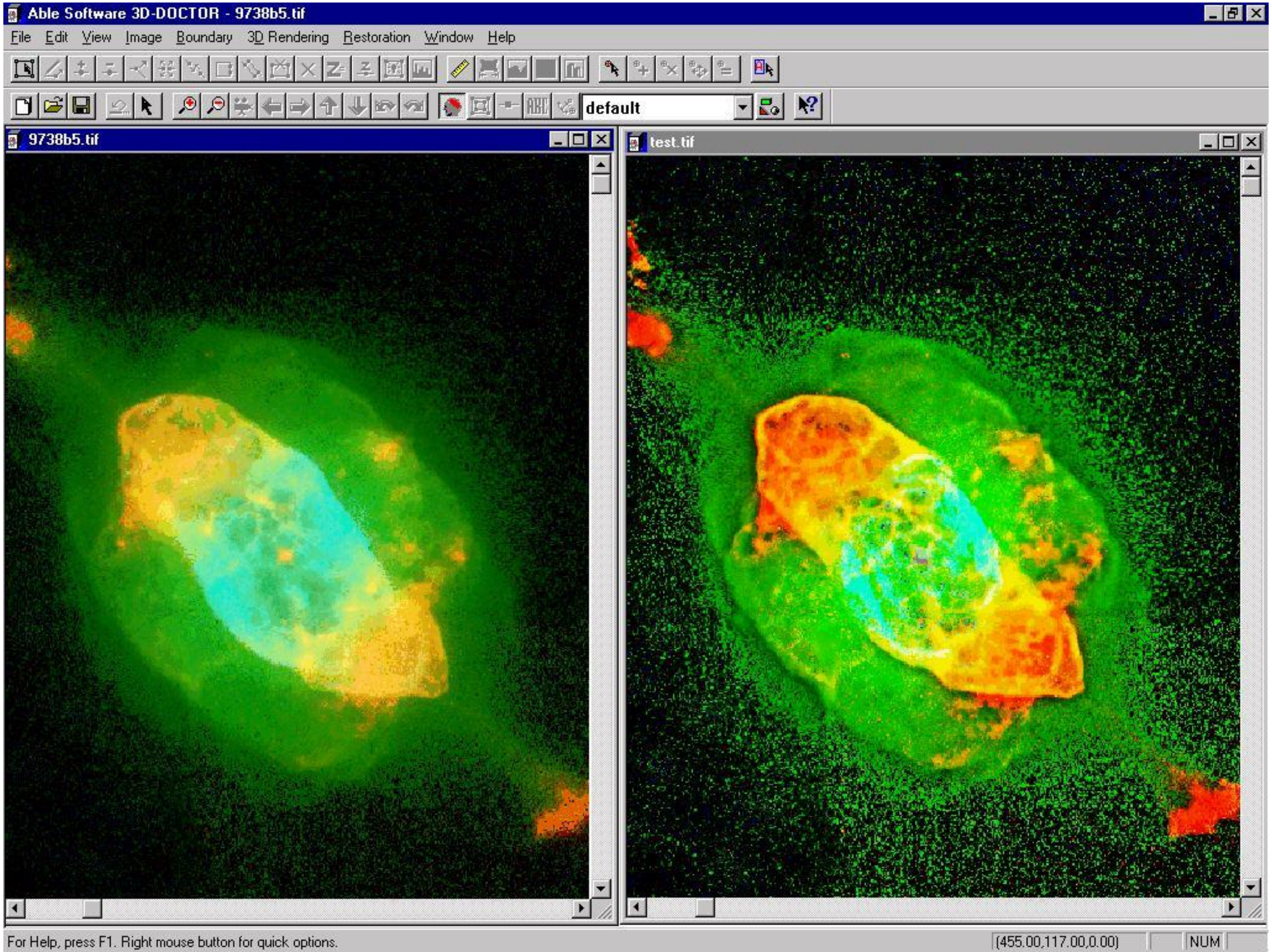
Deconvolution Algorithm Comparison



(a) (b) (c) (d)

Figure 3

3D-DOCTOR: 3D image deconvolution is used to remove or reduce degradations that were incurred while the image was being obtained. These include the blurring introduced by optical systems and by image motion, as well as noise due to electronic and photometric sources: http://www.ablesw.com/3d-doctor/recon.html



$$\mathbf{W} = \mathbf{H} * \mathbf{V} + \mathbf{L}$$

$$\mathbf{R} = \mathbf{W} - \mathbf{H} * \hat{\mathbf{V}} - \mathbf{L} = \mathbf{W} - \mathbf{H} * \mathbf{X} - \mathbf{L}$$

V, W are the M x N input and output images, **H** is the convolution kernel, and ***L*** is the bias. Since eq. is the canonical form of any linear shift-invariant filter, it covers imaging effects such as smoothing of the lens system, first-order optical errors, volume distortion of microscopic target, etc.

If the output of this linear filter is applied to the input of a restoration system, (**W=U**), it transforms the input into the original unfiltered image in the least square error sense, i.e. $\mathbf{X}_{t=\infty} = \hat{\mathbf{V}}$.

This can be proved using the well-known gradient iteration method, considering square norm of R:

$$\mathbf{R} = \mathbf{U} - \mathbf{H} * \mathbf{X} - \mathbf{L}$$

$$\mathbf{G}_X = \frac{d\|\mathbf{R}\|}{dX} = 2\mathbf{H}^r * \left(\mathbf{H} * X - \mathbf{U} + \mathbf{L}\right)$$

Általában a minimalizás regularizációs eljárássá egészül ki:

Hibatag: Becslési hiba + λ * Kényszerfeltétel

- Élek aránya
- Magfüggvény maximalizálása
- Max. Eltérés az eretetitől

Chan T and Wong C-K 1998 Total variation blind deconvolution IEEE Trans. Image Process. 7 370–5

The mathematical formulations that we used in the image recovery problem is stated as follows [12]:

$$\min_u f(u) \equiv \min_u \tfrac{1}{2} \|h \star u - z\|^2_{L^2(\Omega)} + \alpha \int_\Omega |\nabla u| \, dx \, dy \quad (1)$$

where α is a parameter and $\star$ denotes the convolution operator. It is known that TV regularization works effectively for recovering "blocky" images [6].

We formulate the blind deconvolution problem as

$$\min_{u,\,h} f(u,\, h) \equiv \min_{u,\,h} \tfrac{1}{2} \|h \star u - z\|^2_{L^2(\Omega)} + \alpha_1 \int_\Omega |\nabla u| \, dx \, dy + \alpha_2 \int_\Omega |\nabla h| \, dx \, dy. \quad (2)$$

Here α_1 and α_2 are positive parameters which measure the trade off between a good fit and the regularity of the solutions u and h. Such an approach of using TV as a special case of anisotropic diffusion for recovering u and h is also employed

$$\frac{d\mathbf{X}}{dt} = \eta \mathbf{G}_{\mathbf{X}} = -\eta \mathbf{H}^r * \mathbf{H} * \mathbf{X}(t) + \eta \mathbf{H}^r * \mathbf{U} - \eta \mathbf{H}^r \mathbf{L}$$

$$\frac{d\mathbf{X}}{dt} \approx \eta \mathbf{G}_{\mathbf{X}} = -\eta \mathbf{H} * \mathbf{X}(t) + \eta \mathbf{U} - \eta \mathbf{L}$$

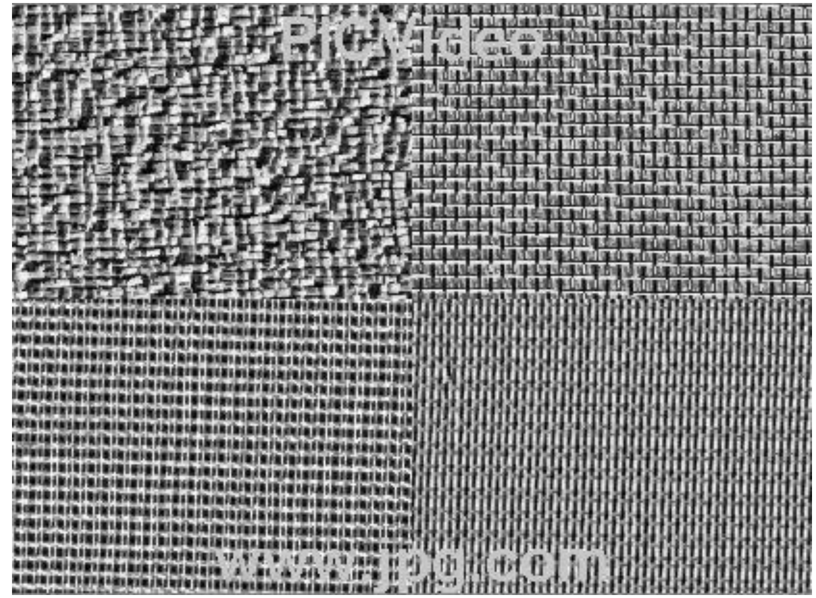
$$\mathbf{X}(t+1) \approx \mathbf{X}(t) - \mathbf{H} * \mathbf{X}(t) + \mathbf{U}, \qquad \mathbf{L}=0,\ \eta=1,\ \mathbf{X}(t) = \mathbf{U}$$

ÚjraBecsült = Becsült - **H** $*$ Becsült + Mért

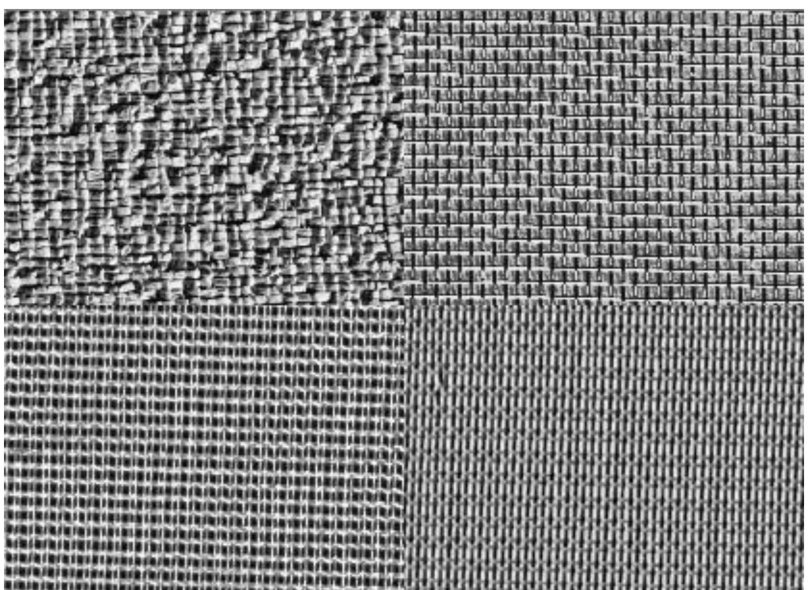
Here the $\mathbf{H}^r$ convolution-matrix comes from a 180^o rotation of the convolution-matrix **H**. This gradient can be used in an infinite iteration process in calculating **X** (IIR convolution filter). This time-dependent approximation process is given by the state-equation.

$\mathbf{H}^r * \mathbf{H}$ in the feedback is always stable if its system block-matrix ($\mathcal{H}^T\mathcal{H}$) given by the $\mathcal{H}$ hypermatrix of the **H** convolution-matrix is nonsingular.

A visszacsatolt konvolúciót tartalmazó CNN egyidejűleg különböző műveleteket képes elvégezni, mint: konvolúció, dekonvolúció, mozgatás, korreláció és féltónusos kimenet, és ezzel különösen alkalmas képi textúrák analízisére.



Dinamikus szűrés, genetikus algoritmussal előállított paraméterekkel

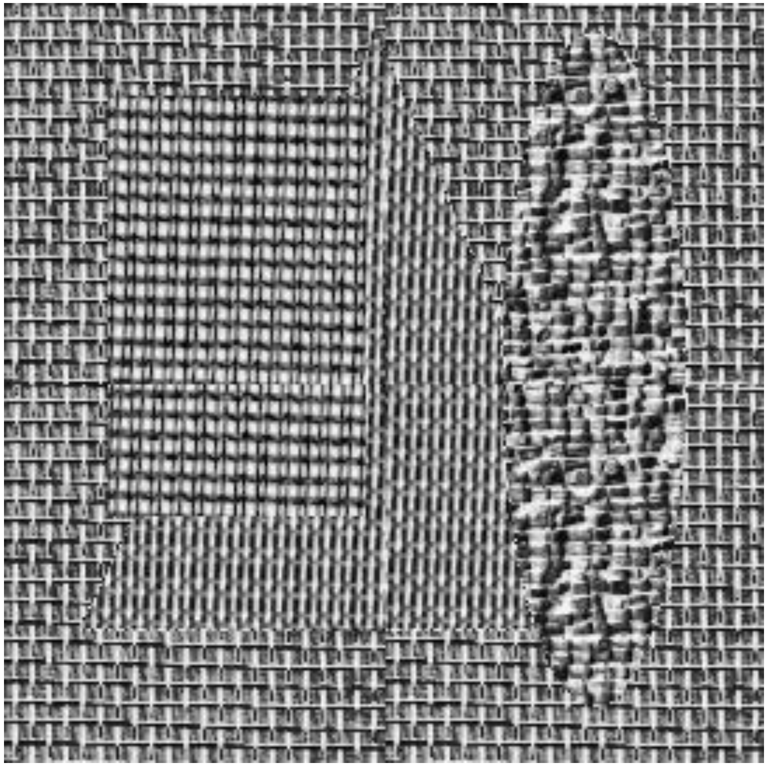


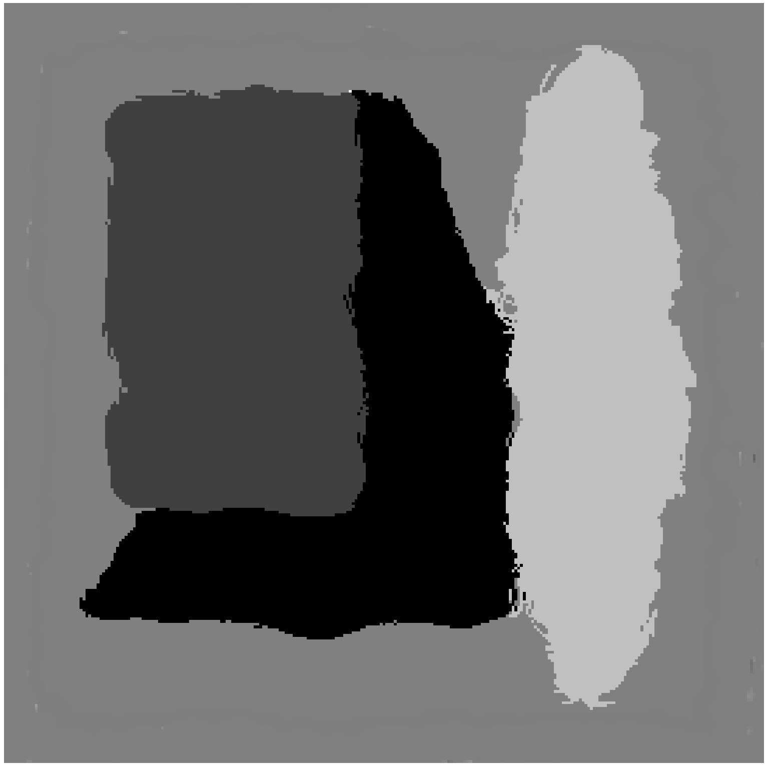
4 bemeneti textúra

Textúra szegmentálás

bemeneti textúra

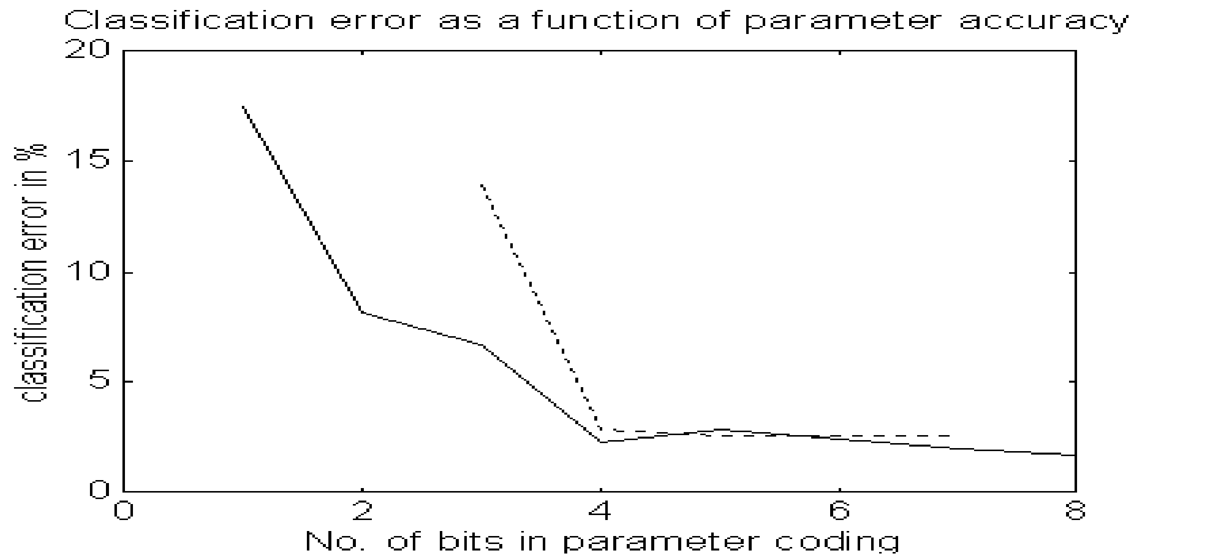
Szegmentált eredmény
4 szűrés eredményeinek
összevetésével

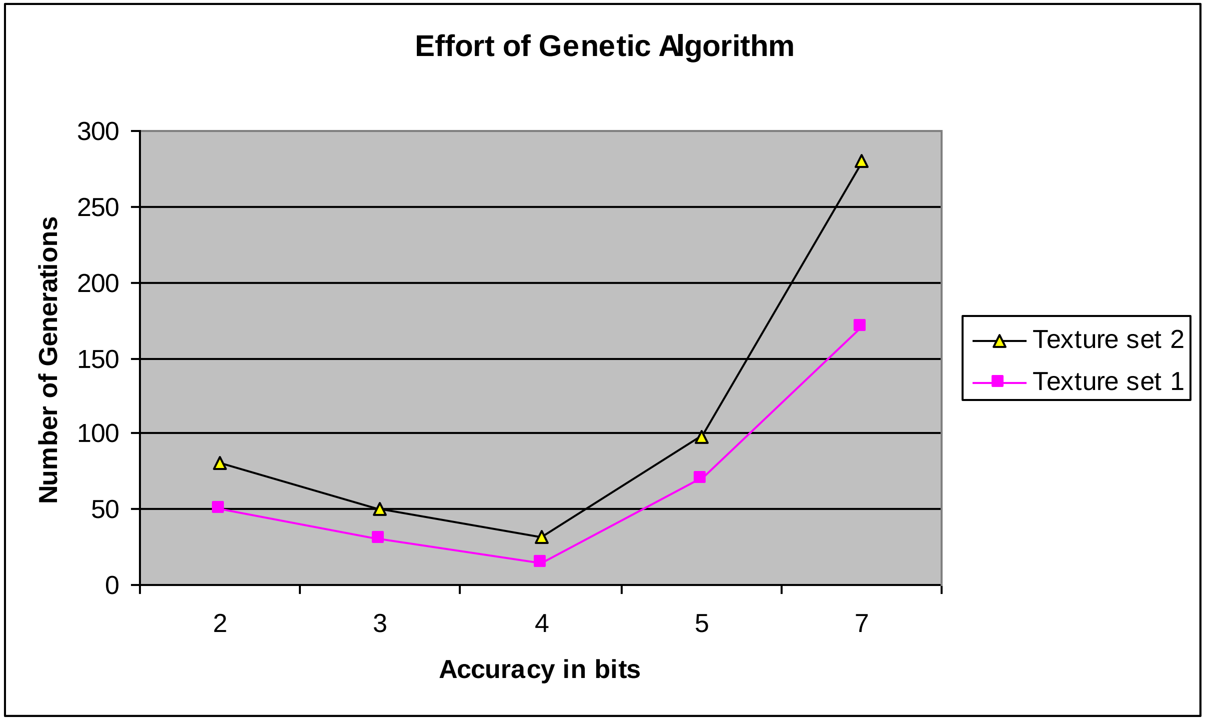


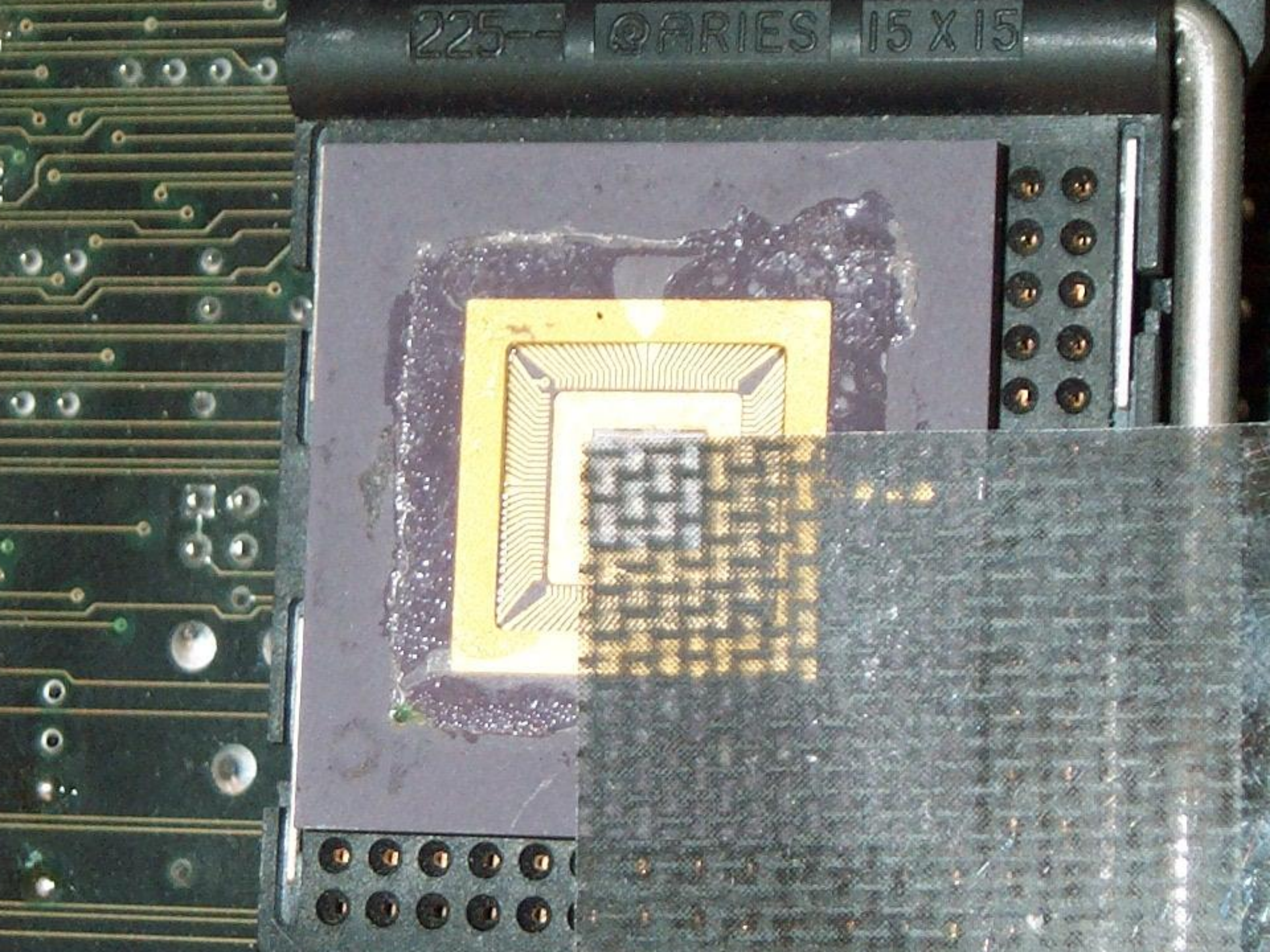


Robusztusság:

- Paraméterpontosság
- Optimalizálási idő



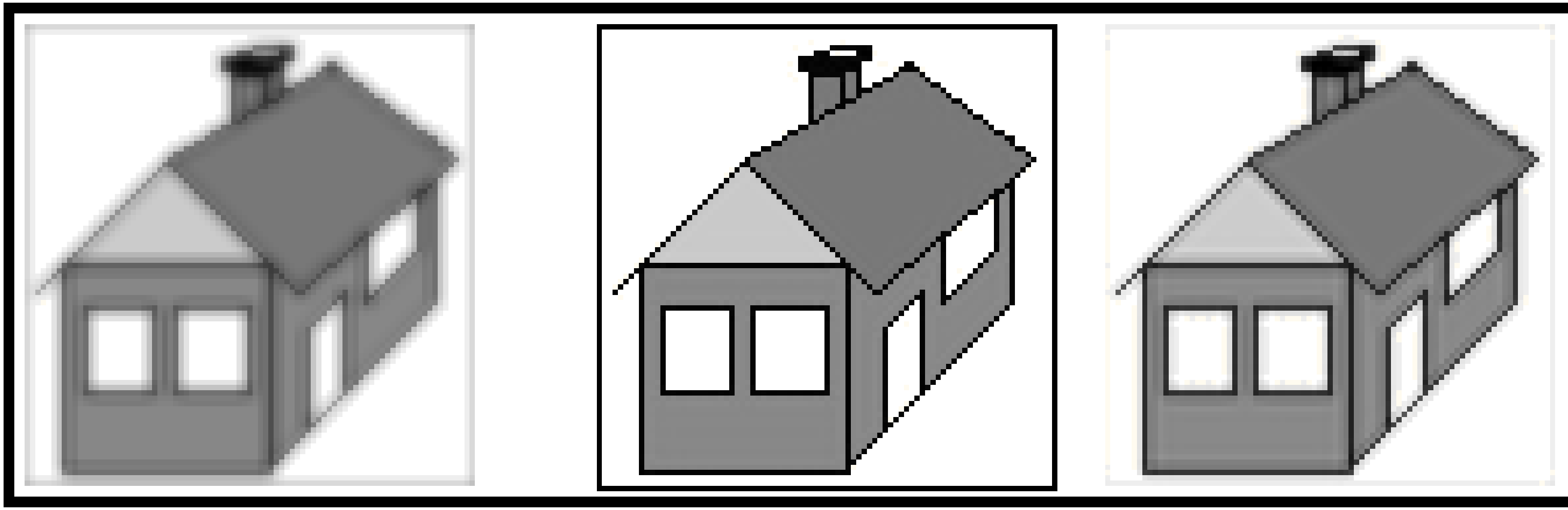



225
ARIES
15 X 15

Textúra felismerés a 64x64 CNN lapkán

A bemeneten 4 különböző mintázatot tapogatunk le

Szűrés után a bevett kép átlagos árnyalata a mintázat típusára lesz jellemző



Blurred image of a drawing with ***H*** of Table 1 (left); Reconstruction by **H** (mid) up to 30% variation in the parameters of **H** (right)

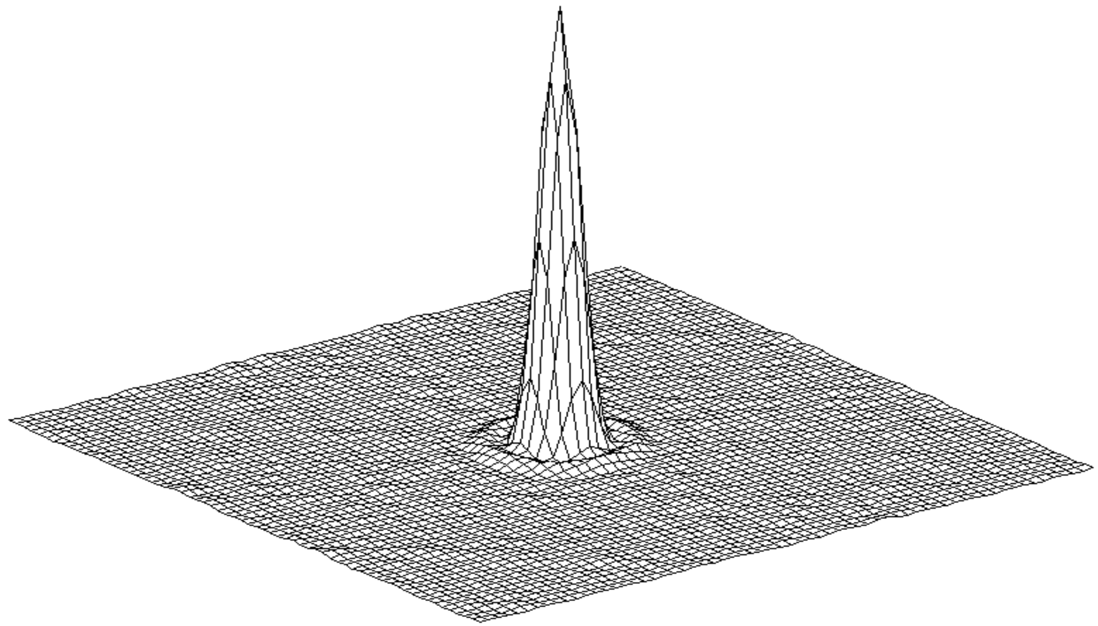
Speciális esetek a stabil konvergenciára

$$\mathbf{H} = \mathbf{H}_1^{\mathbf{r}} * \mathbf{H}_1 \qquad \mathcal{H} = \mathcal{H}_1^T \mathcal{H}_1$$

$$\mathbf{H} = \mathbf{H}_y * \mathbf{H}_x^T \qquad \mathcal{H} = \mathcal{H}_x^T \otimes \mathcal{H}_y$$

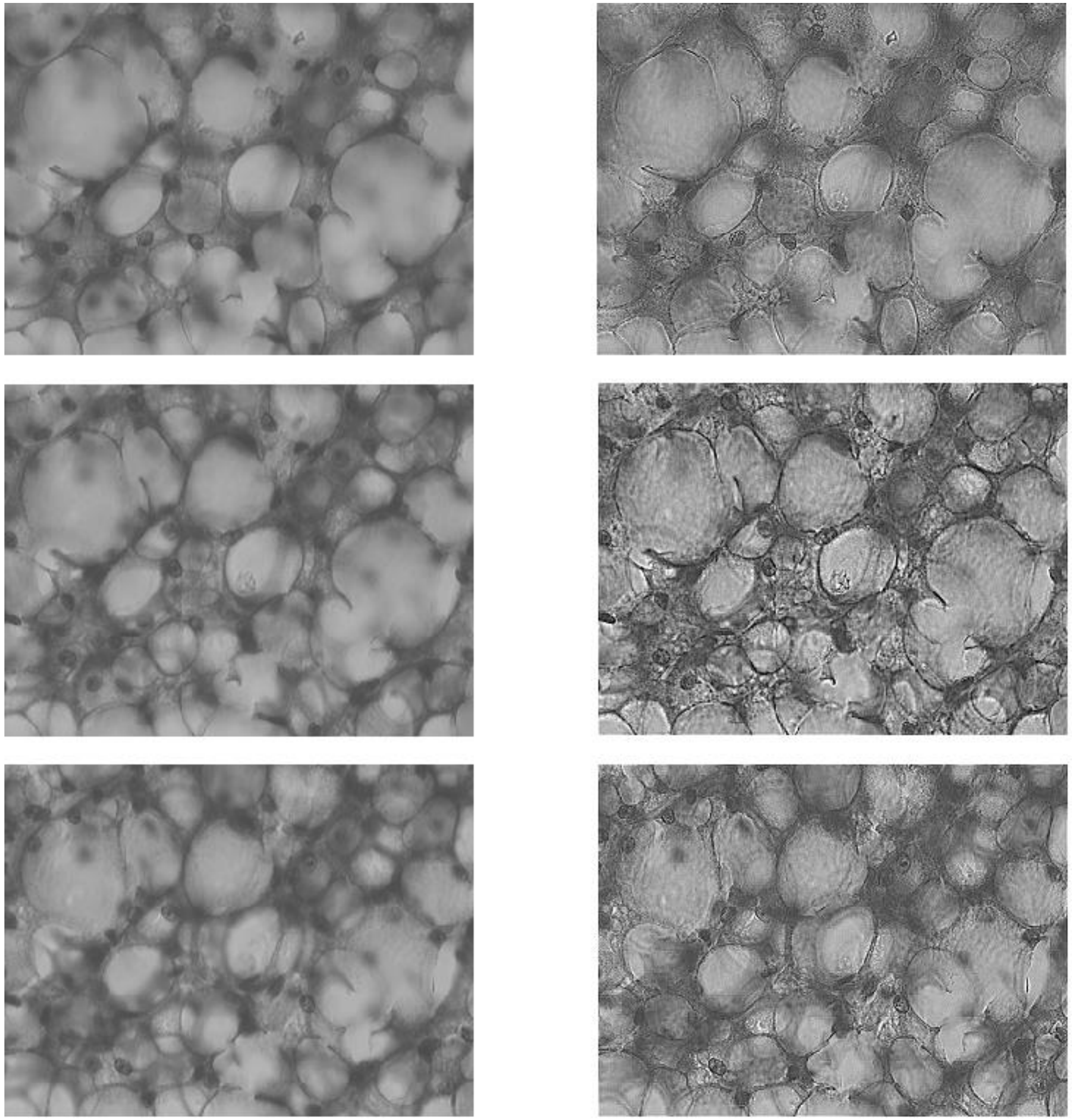
In the stack matrix notation the elements of the separable PSF can be written into Kronecker direct product.

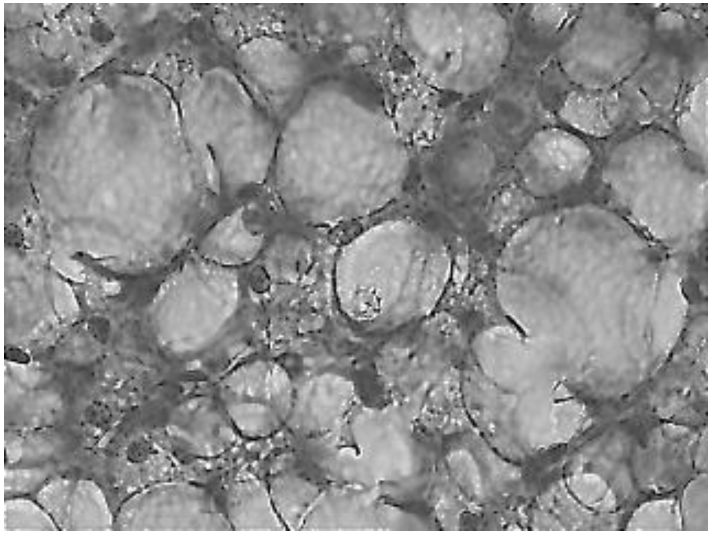
Since the eigenvalues of the Kronecker product are the products of the eigenvalues of the simple matrices, in case of positive definite matrices the resulting product term will also be positive definite. This implies a very weak constraint for the circular PSF.



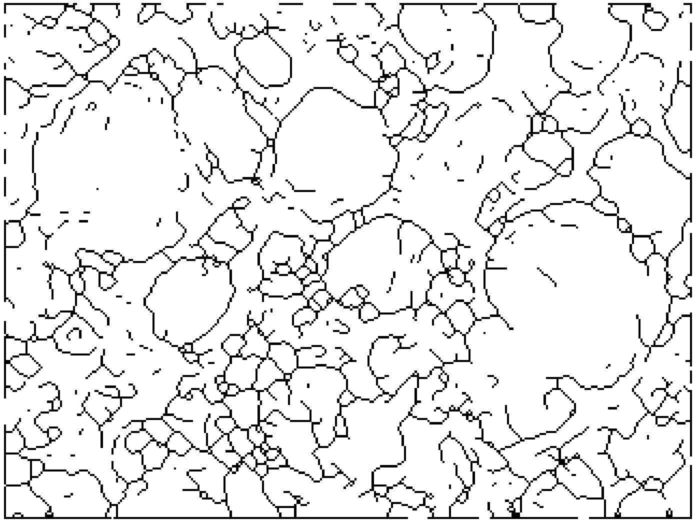
The 3D Point Spread Function of a defocused system as a function of the *r* and *z* co-ordinates

$$h(R,Z) = \Im_2\{P(\rho,z)\} = \Im_2\{e^{[i(2\pi/\lambda)\sigma(z)(\rho/\rho_o)^2]} circ(\rho/\rho_0)\}$$



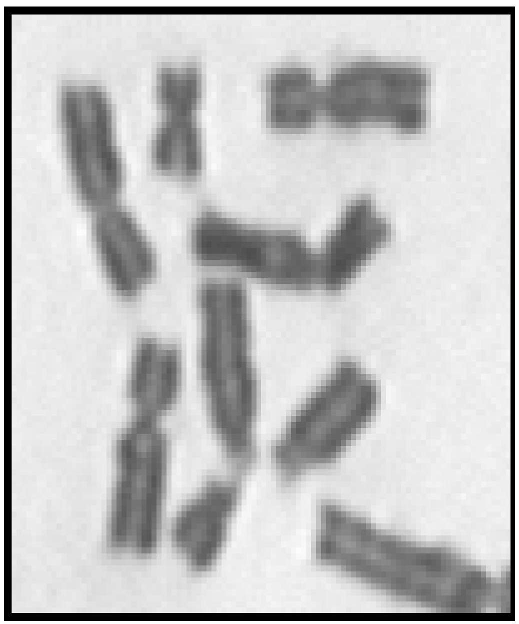


Anisotropic Diffusion based edge enhancement and noise removal on the mid-layer



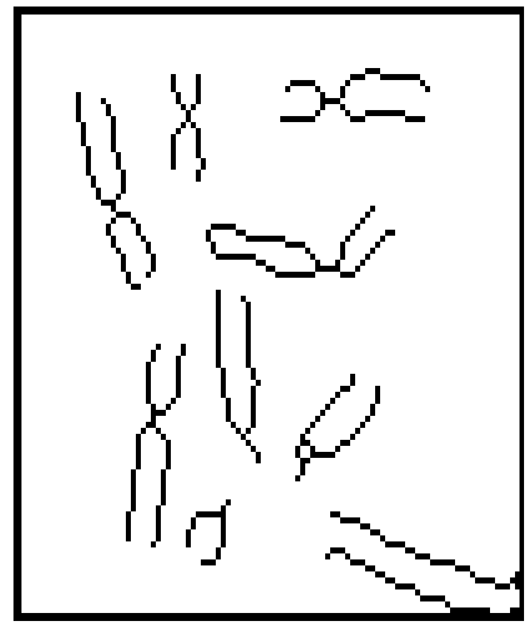
The skeletonized edge map of the microscopic mid-layer

Két- és három-dimenziós dekonvolúció visszacsatolt konvolúciós tér-szűrővel



Eredeti

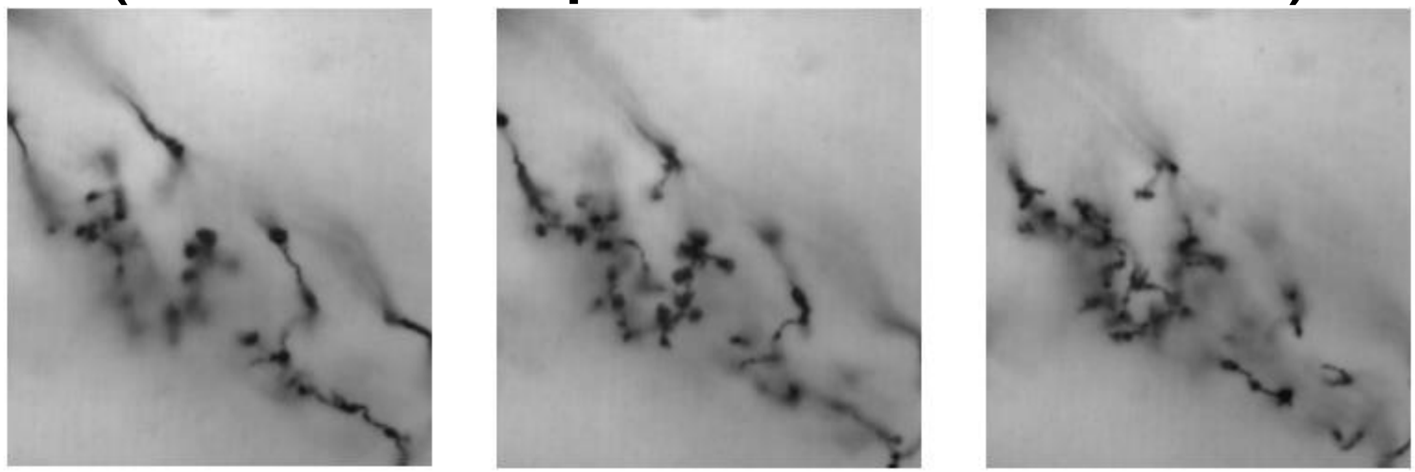
Kiélesített



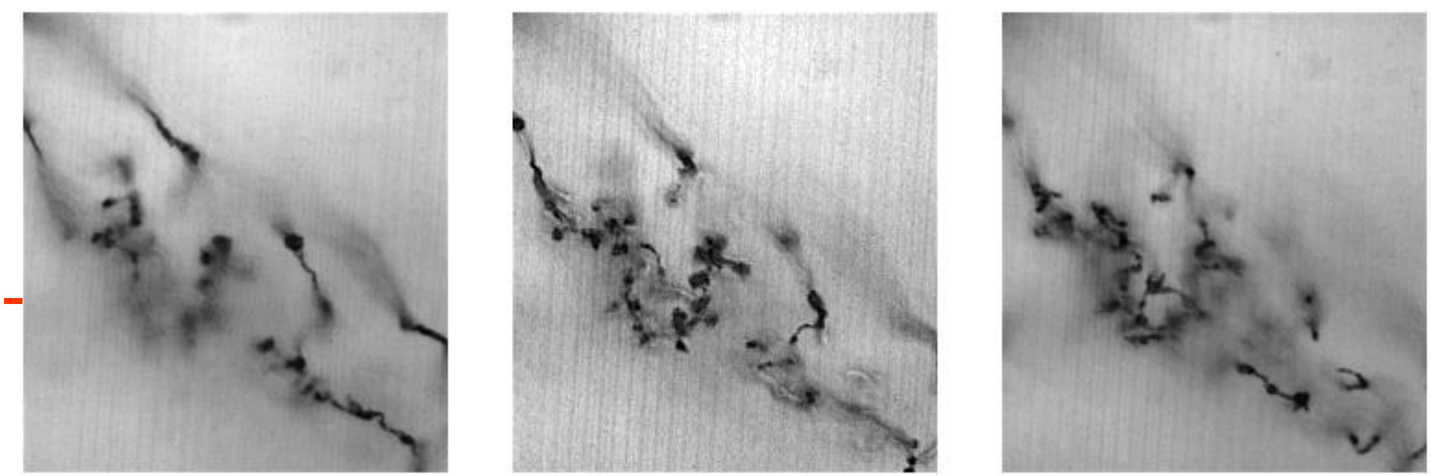
Vázosított

Kép mélységi élesítése
(Mikroszkópi felvételsorozat)

Látott kép-sorozat



Kiélesített számítógépes eredménykép-sorozat



Blind Deconvolution
Vak dekonvolúció

- Valószínűségi Bayes modell
- Kapcsolat az energialeloszlás és az optikai átviteli függvény (PDF) között
- Kettős iteráció a
  - A konvolúciós hatás
  - A kép

    Együttes becslésére
- Becslés a fókusz térképre

Focus estimation with deconvolution

- Blind deconvolution:
  - Given observation g, give an estimation of the original image f and the blurring function (PSF) h : $g = f * h$
  - Starting from Richardson's original formula based on Bayesians:

$$P(f_i|g) = [P(g|f)P(f_i)] \,/\, \sum_j [P(g|f_j)P(f_j)]$$

$$P(f|g) = P(fg)/P(g)$$

$$P(f_i) = \sum_l P(f_i g_l) = \sum_l P(f_i|g_l)P(g_l) = \sum_l \frac{P(g_l|f_i)P(f_i)P(g_l)}{\sum_j P(g_l|f_j)P(f_j)}$$

$$P_{k+1}(f_i) = P_k(f_i) \sum_l \frac{P(g_l|f_i)P(g_l)}{\sum_j P(g_l|f_j)P_k(f_j)}$$

Blind deconvolution with Lucy - Richardson double irerations

$$f_{i,k+1} = f_{i,k} \sum_l \frac{h_{i,l} g_l}{\sum_j h_{j,l} f_{j,k}} = f_{i,k} \sum_l h_{i,l} \frac{g_l}{\sum_j f_{j,k} h_{j,l}}$$

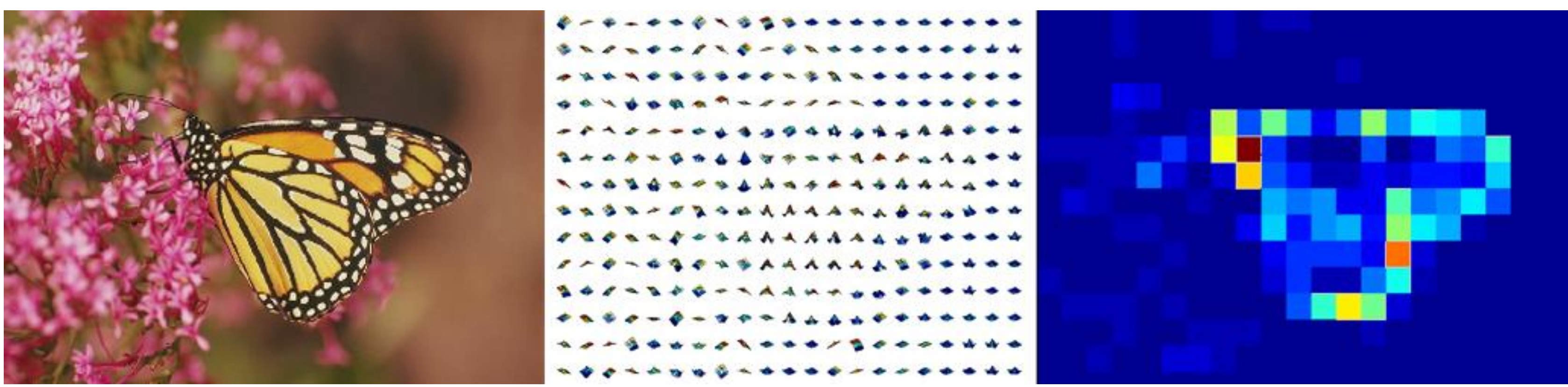
$$f_{k+1} = f_k \left(h_k \otimes \frac{g}{f_k \otimes h_k} \right)$$

The double iteration

- We create a localized double iteration scheme for locally varying *f* and PSF estimation (*r* – location vector):

$$\begin{cases} f_{k+1}(r) = f_k(r) \left[h_k(r) * \frac{g}{g_k}(r) \right] \\ h_{k+1}(r) = \frac{h_k(r)}{\gamma} \left[f_k(r) * \frac{g}{g_k}(r) \right] \end{cases}$$

- *f* and the PSF vary locally according to the amount of blur (distortion) present on the image locally
- Stop the double iteration at a finite step (here #5) and check the **error between the measured and the estimated blurred image** blocks: $\| g - g_k \|$
- Is MSE usable for comparison the BD residual errors of different blocks?



Constraints and ill-posedness

- In the local deconvolution we consider only a few constraints
  - symmetricity,
  - non-negativity,
  - zero phase.
  - and **nothing** about the image content **regularization** (e.g. edges). Localized deconvolution runs on small blocks, range of the PSF. Thus the ill-posed iteration process tends to be **noisy**.
- For the classification we stop at a low iteration count and we need a stable error measure which gives different values for differently focused areas, and which is not much affected by the process's noisy nature.

ADE : angle deviation error

Orthogonality criterion: signal and noise are independent

$$\left| \arcsin \frac{\langle g, g - g_k \rangle}{|g| . |g - g_k|} \right|$$

In case of

$g - g_k = [+1, -1, -1, +1, -1, +1 ...... -1, +1]$

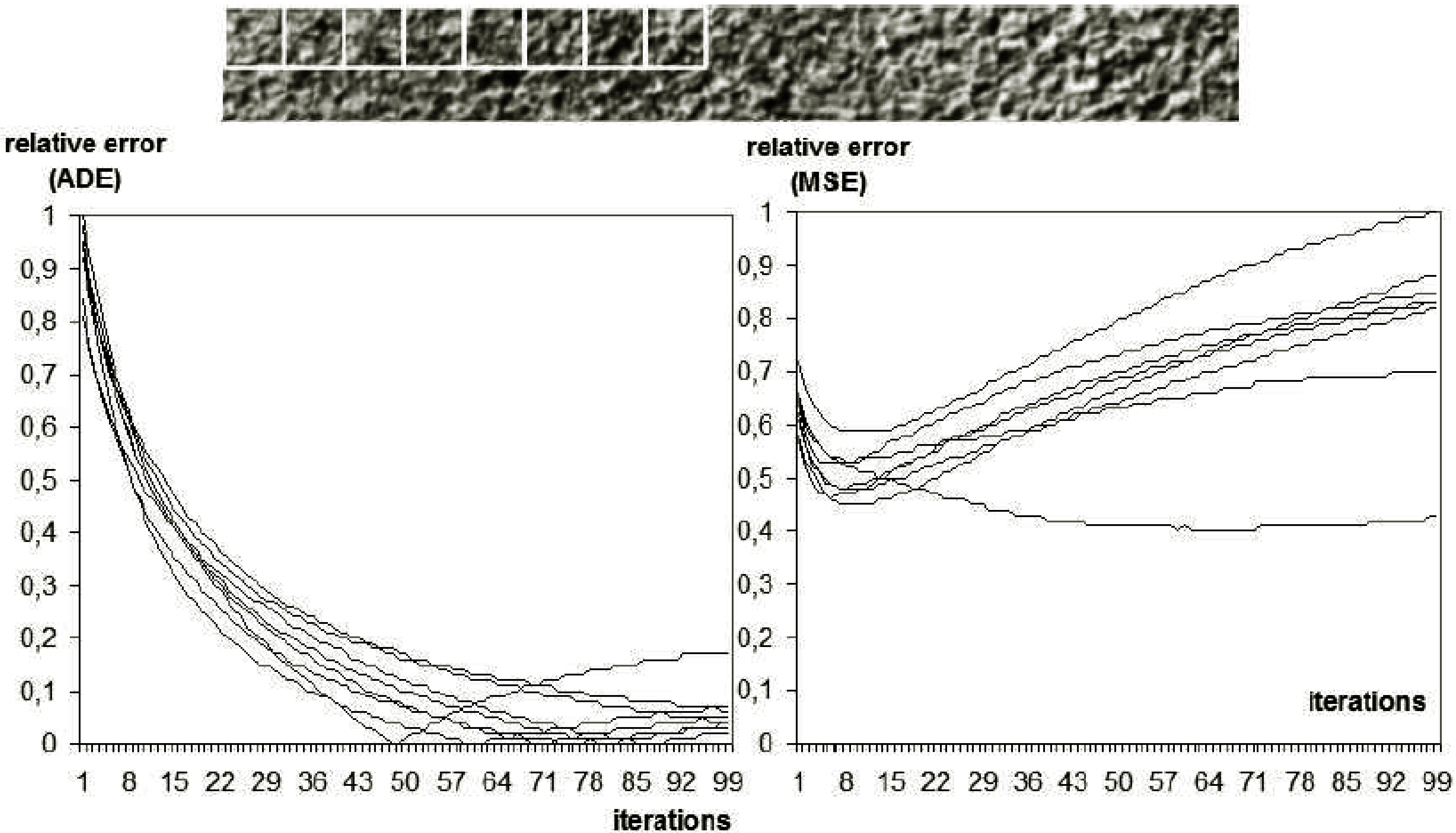
$g = [10, 10, 10, 10, 10, 10 ..... 10, 10]$

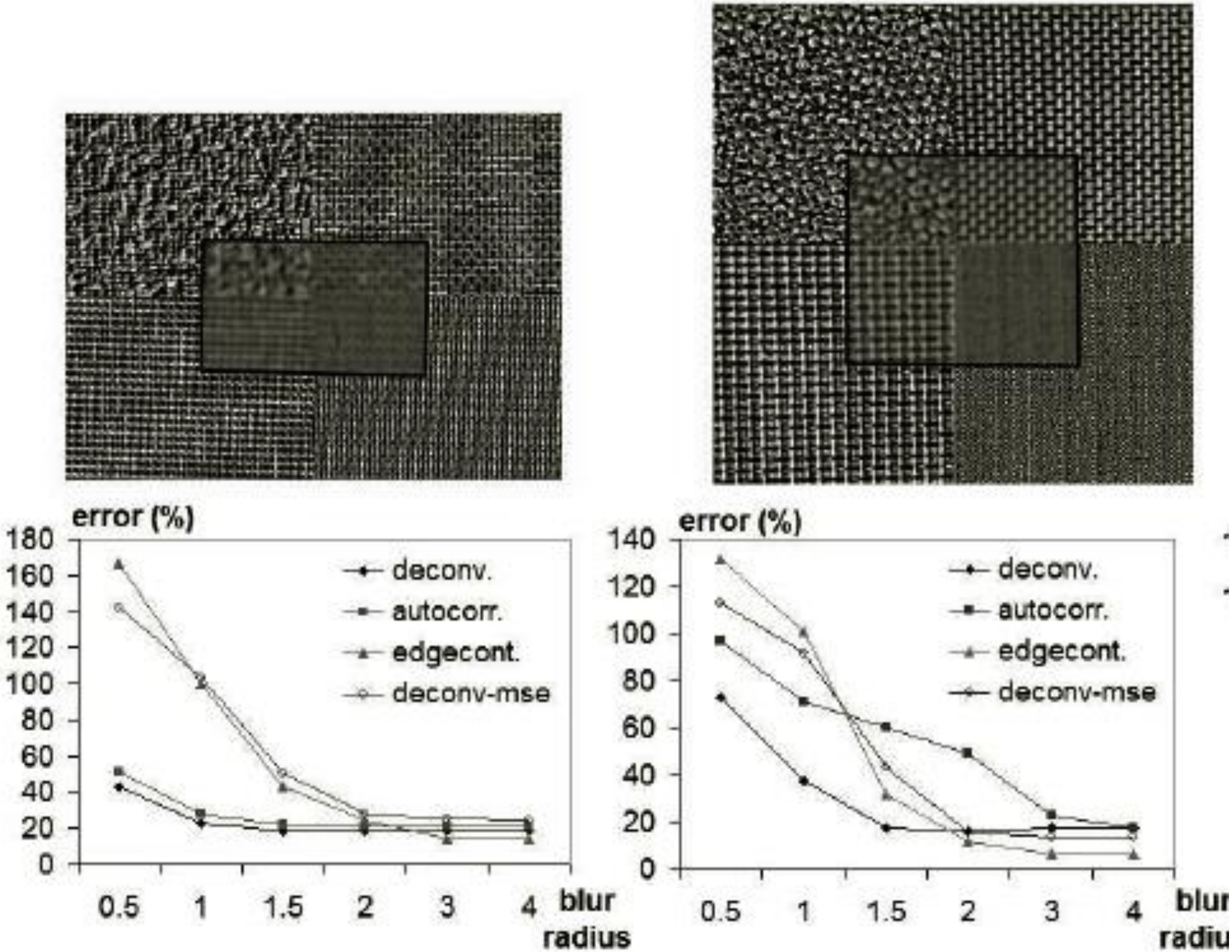
$\| g - g_k \|$ is high, while

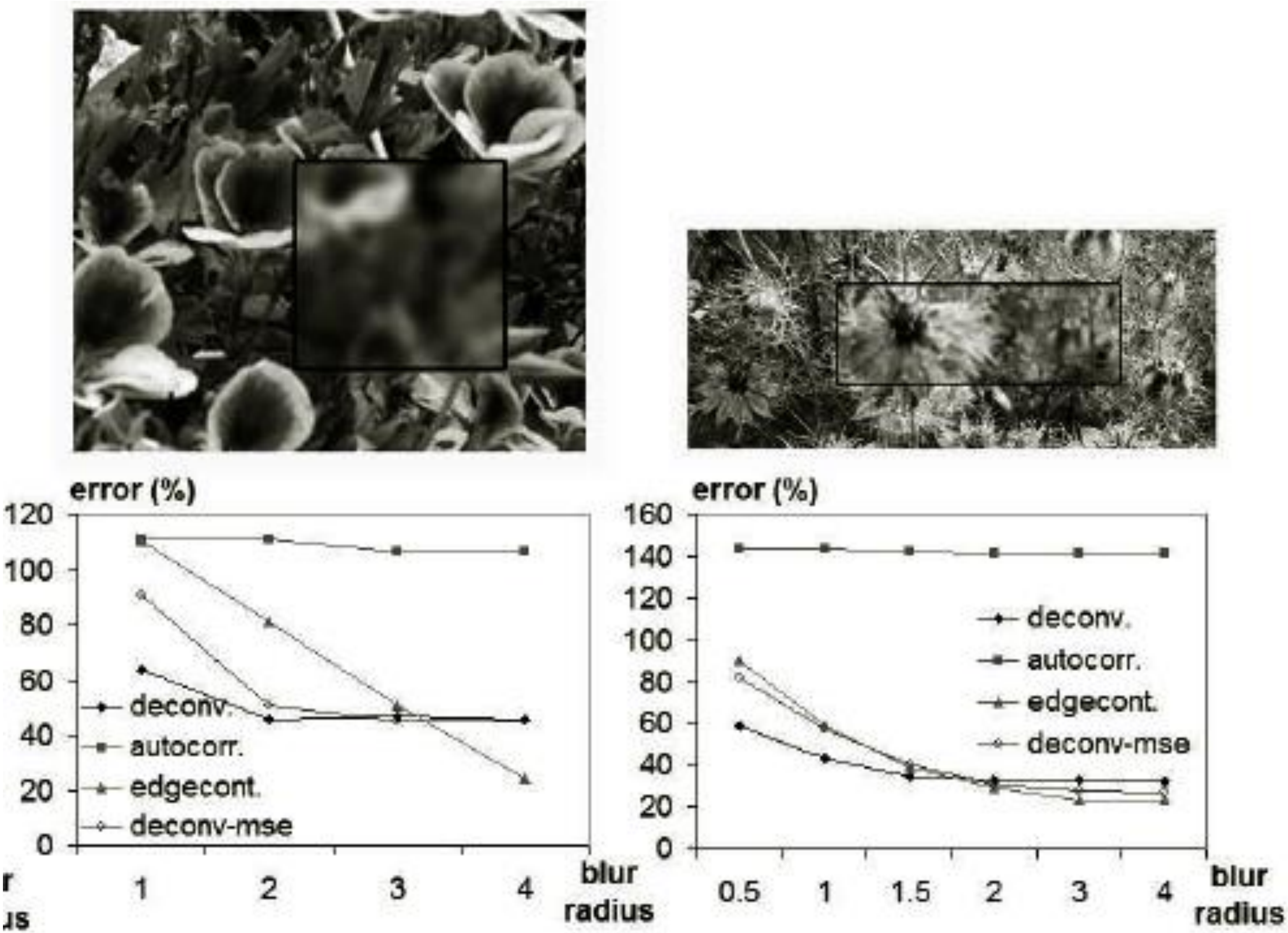
$< g, g - g_k > \longrightarrow$ zero

Error curves for 8 neighboring blocks (each curve stands for one block) on a blurred texture sample (top) for the same blur with ADE **(left), and** MSE **(right) .**

Ideally, curves of the same measure should remain close to each other.




error (%)
180
160
140
120
100
80
60
40
20
0
deconv.
autocorr.
edgecont.
deconv-mse
0.5
1
1.5
2
3
4
blur
radius
error (%)
140
120
100
80
60
40
20
0
deconv.
autocorr.
edgecont.
deconv-mse
0.5
1
1.5
2
3
4


error (%)
120
100
80
60
40
20
0
deconv.
autocorr.
edgecont.
deconv-mse
1
2
3
4
blur radius
error (%)
160
140
120
100
80
60
40
20
0
deconv.
autocorr.
edgecont.
deconv-mse
0.5
1
1.5
2
3
4
blur radius

Find images with similar relative focused objects:

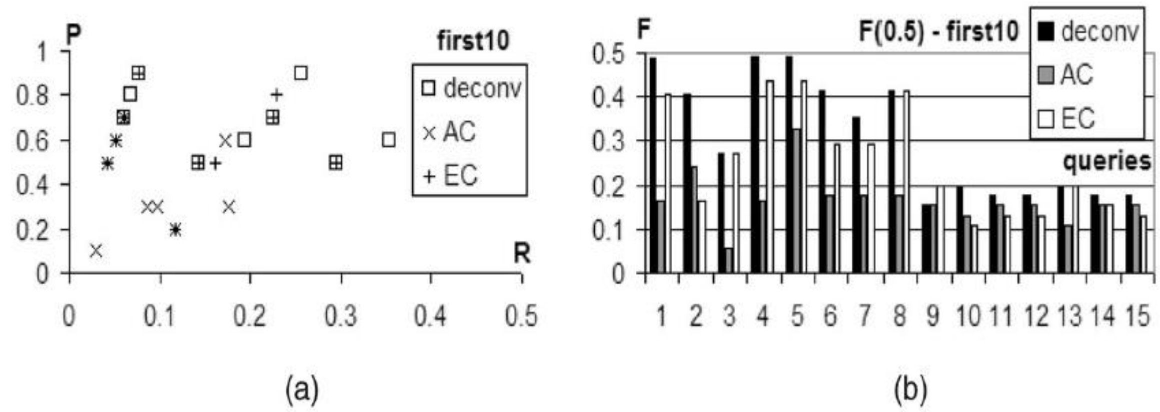


Fig. 14. Precision-Recall graph for 15 queries: (a) The returned closest 10 matches and (b) $F(0.5)$ measure values (higher is better).

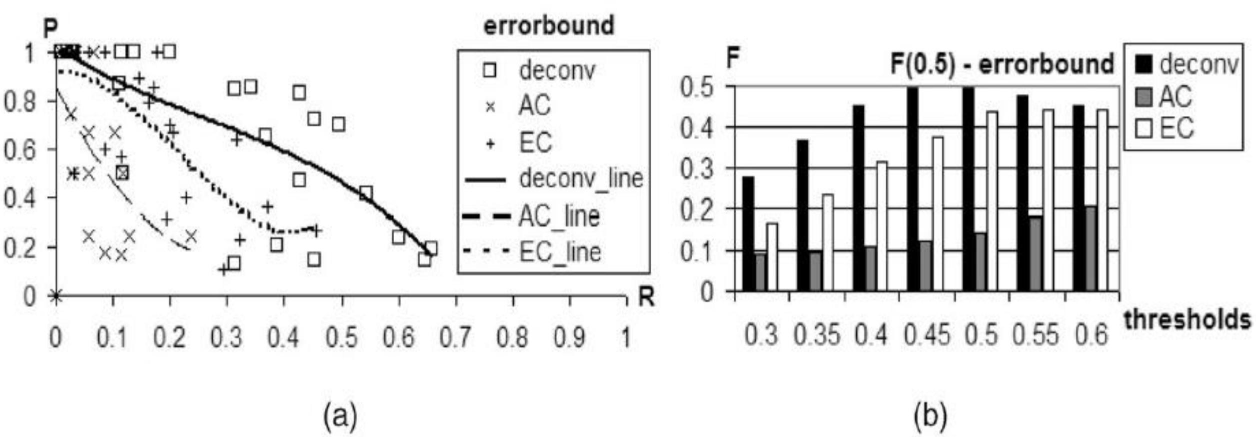
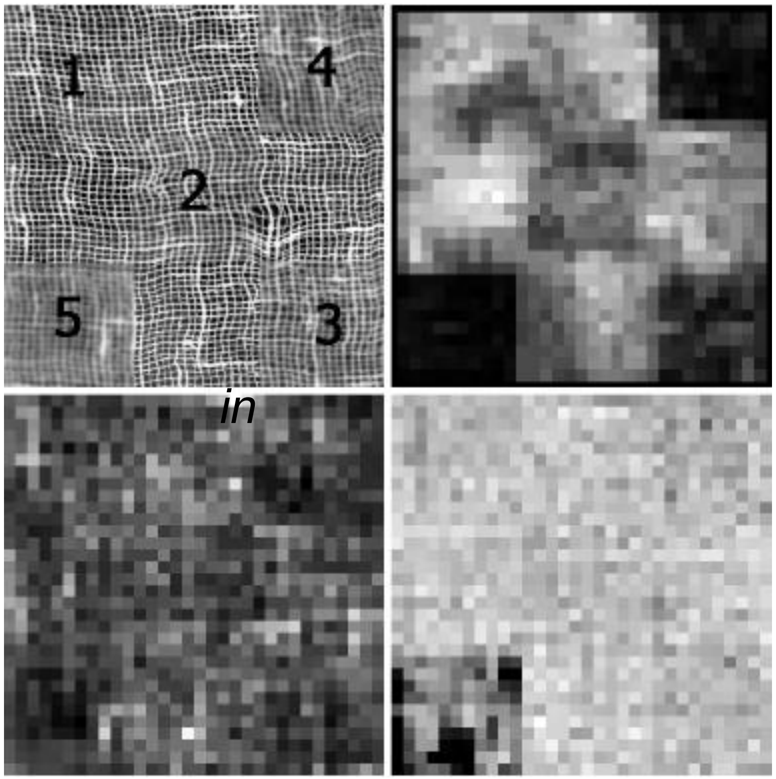
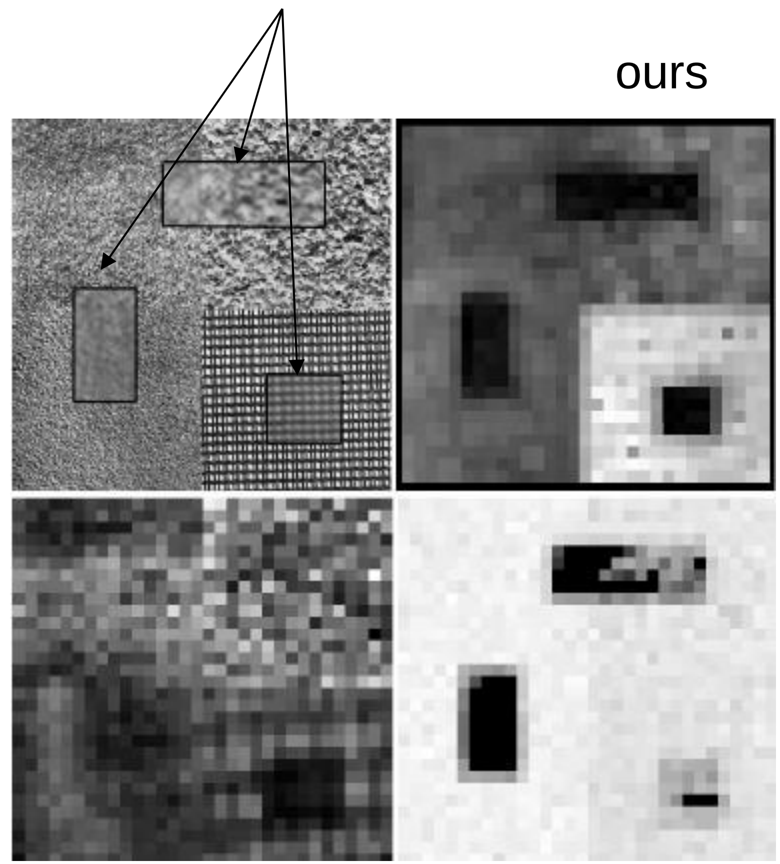


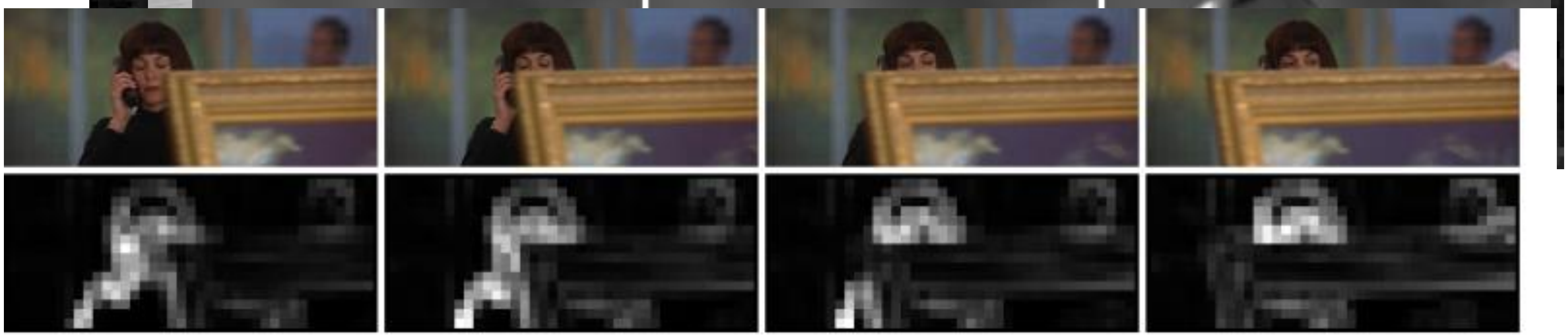
Fig. 15. (a) Averaged Precision-Recall curves for returning every match above a threshold (*errorbound* approach) for the 15 query images and (b) the respective $F(0.5)$ measure values for the different thresholds (higher is better).

- Relative focus maps

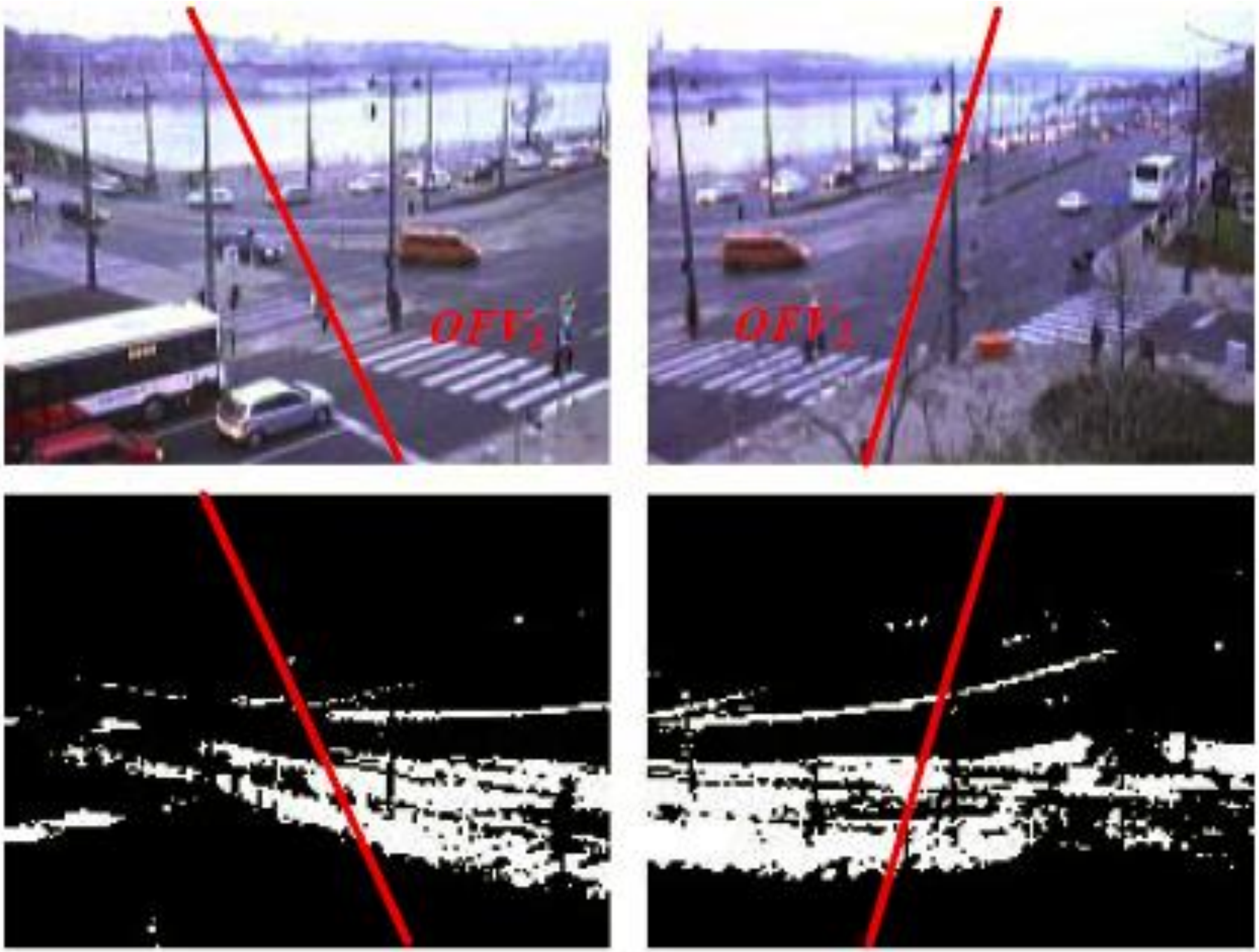
- Rel. focus map extraction - comparison on textures







Samples from input videos and
Results of the *entropy* based preselection of feature points



Probabilistic interaction among points of different views for motion / no-motion functions

$$P(m_{1i} \mid m_{2k}) = \frac{1}{\sum_{t=1}^{T} \underline{b}_{2k}(t)} \sum_{t=1}^{T} \underline{b}_{1i}(t)\underline{b}_{2k}(t)$$

$$P(m_{1i} \mid m_{2k}) = \frac{P(m_{2k} \mid m_{1i})P(m_{1i})}{\sum_{j} P(m_{2k} \mid m_{1j})P(m_{1j})}$$

Ergodic regular Markov chain has a unique stationary distribution

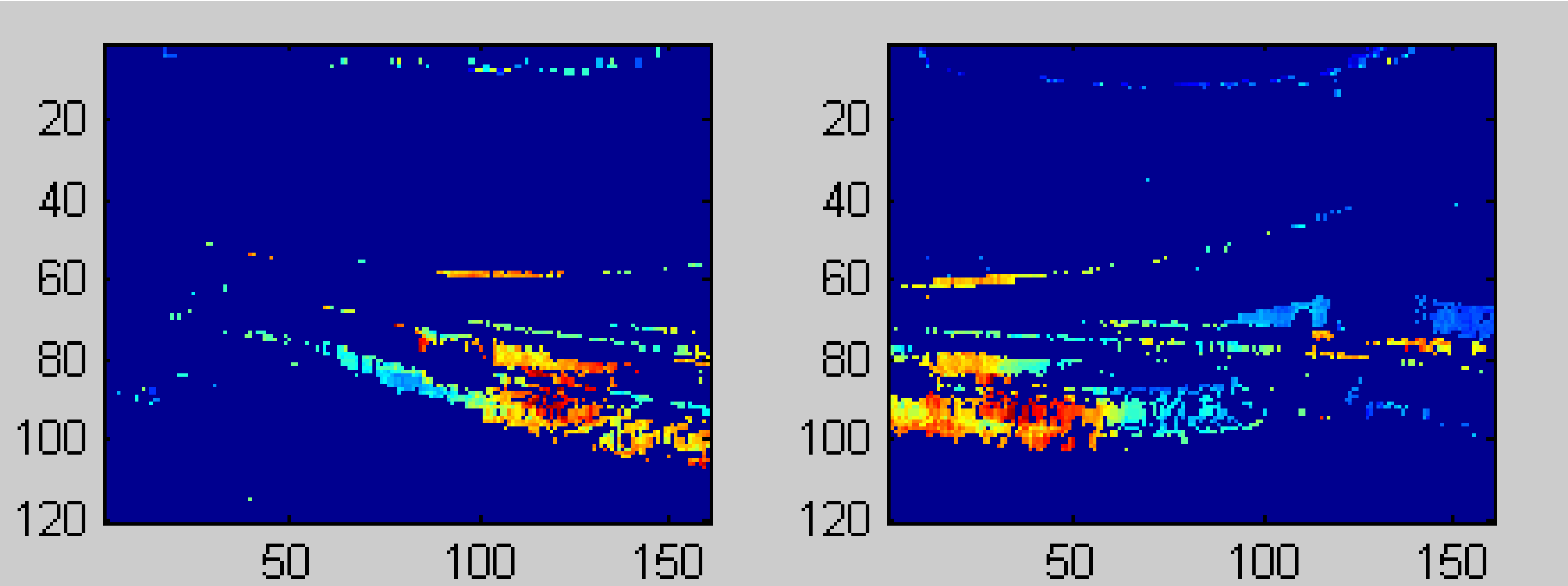
$$\left(\underline{p}_1 \quad \underline{p}_2\right) = \left(\underline{p}_1 \quad \underline{p}_2\right)\underline{\underline{\Pi}}$$

$$P(m_{1i})_{r+1} = P(m_{1i})_r \sum_k \frac{P(m_{2k} \mid m_{1i}) P(m_{2k})_r}{\sum_j P(m_{2k} \mid m_{1j}) P(m_{1j})_r}$$

$$P(m_{2k})_{r+1} = P(m_{2k})_r \sum_i \frac{P(m_{1i} \mid m_{2k}) P(m_{1i})_r}{\sum_j P(m_{1i} \mid m_{2j}) P(m_{2j})_r}$$

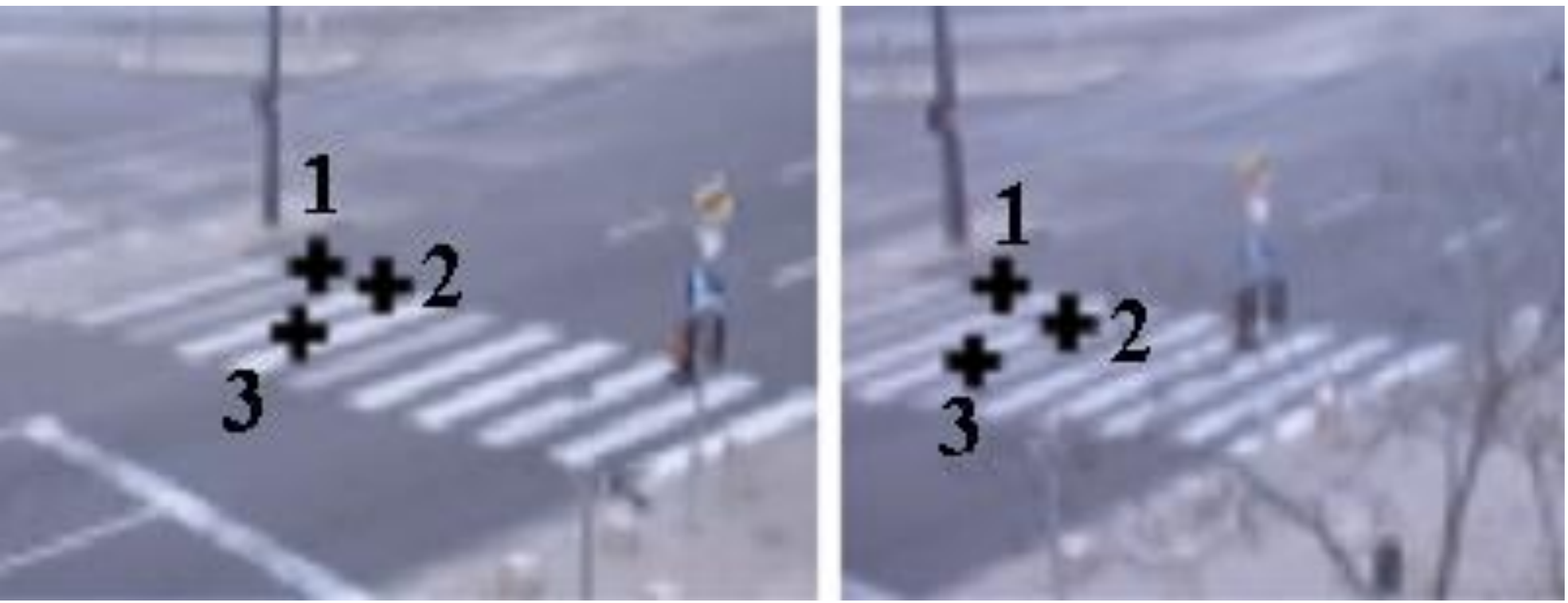
Bayesian iterations of Ergodic regular Markov chain

with a unique stationary distribution



Sample point pairs obtained by Bayesian iterations.

The nearly corresponding points are numbered with the same number.



The error function

- Localised blind deconvolution for focus map estimation:
  - run local deconvolution with a low iteration count
  - calculate local residual errors, with contrast weighting

$$E_r(g, g_k) = arc\ sin \frac{< g - g_k, g >}{|g - g_k| \cdot |g|} \cdot \frac{C_r(g_r)}{max_r \{C_r(g_r)\}}$$

$$C_r(g_r) = \frac{g_{max\{x \in T_r\}} - g_{min\{x \in T_r\}}}{g_{max\{x \in T_r\}} + g_{min\{x \in T_r\}}}$$

  - use the local residuals for relative classification of areas

$$F(r) = \frac{c \cdot (E_r(g, g_k) - min\{E_r(\cdot, \cdot)\})}{max\{E_r(\cdot, \cdot)\} - min\{E_r(\cdot, \cdot)\}}$$