Correlation-Based Deblurring Leveraging Multispectral Chromatic Aberration in Color and Near-Infrared Joint Acquisition

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Presented by Majed El Helou

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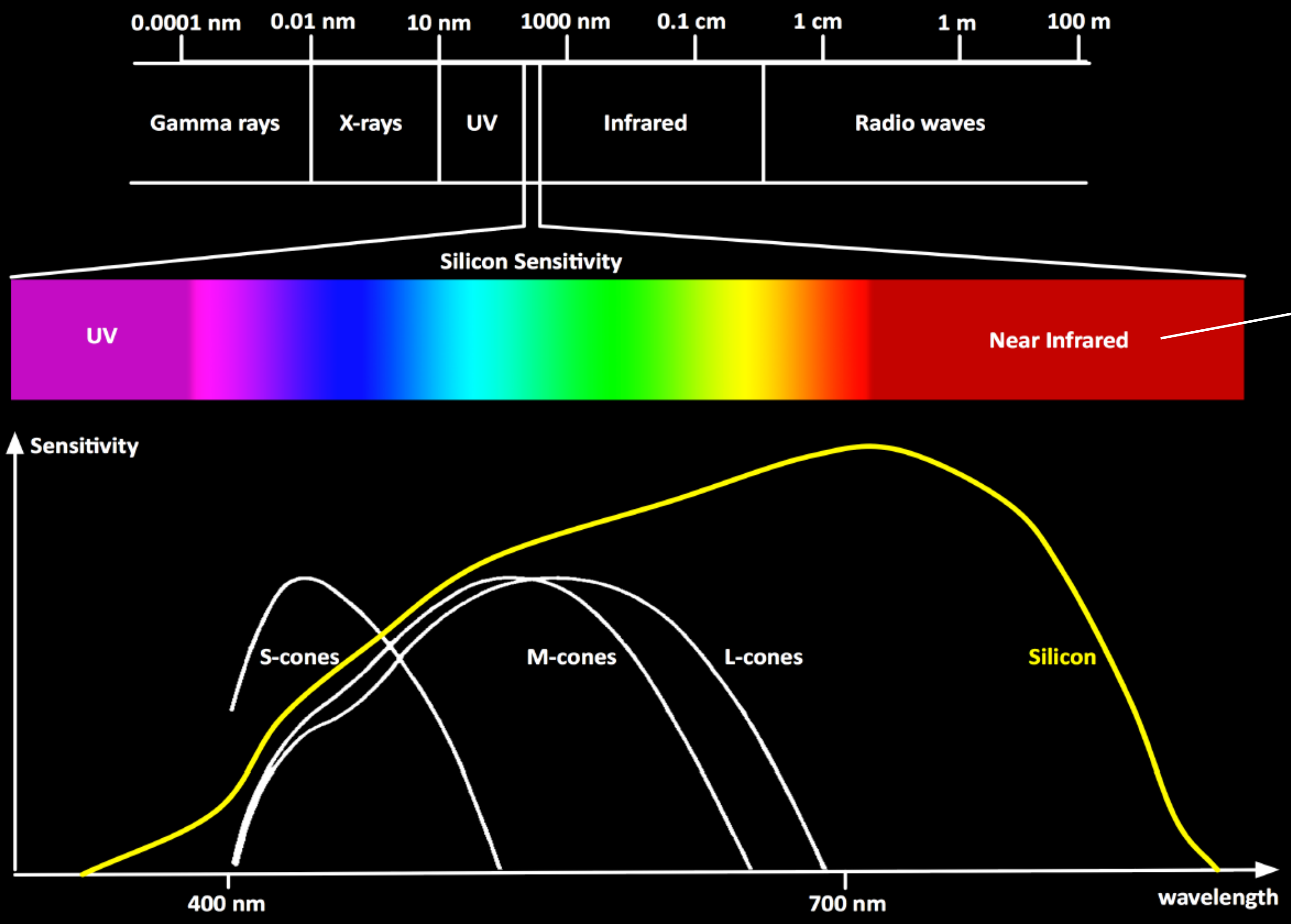
ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

NIR and its acquisition

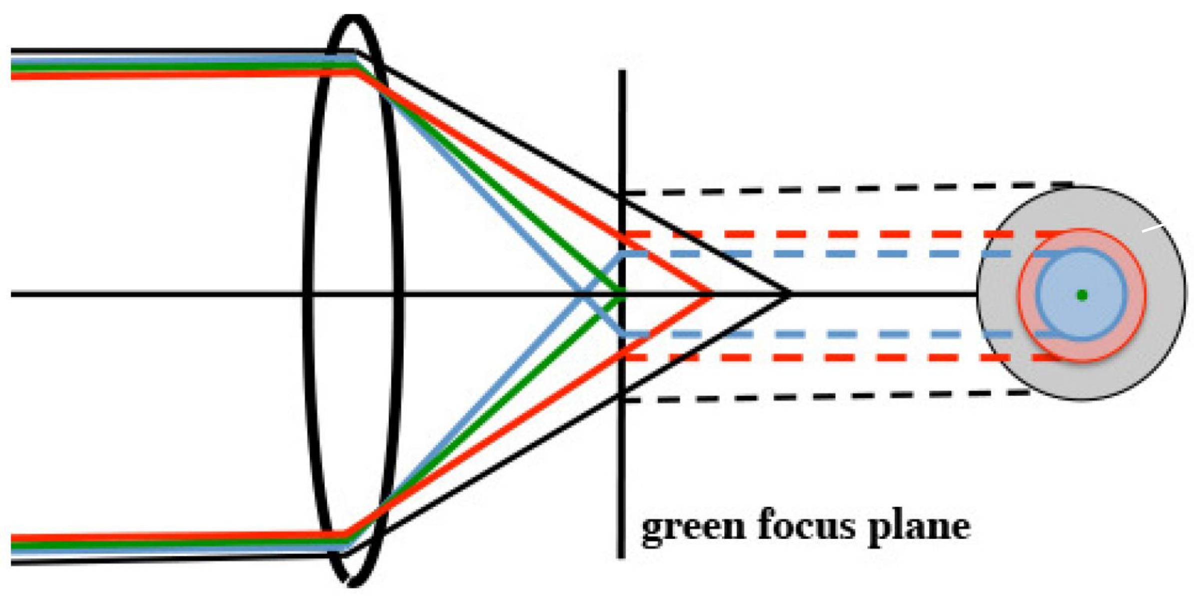


≈ 700 - 1000nm

Some applications

- Haze detection and removal
- Shadow detection
- Skin smoothing
- Material-based segmentation
- Vegetation detection
- Face authentication
- …

Chromatic aberration (longitudinal)



circle of confusion

Different wave bands converge at different focal points!

➡ Only one is captured in focus*

*Unless the camera resolution is even lower than the blur radius

Chromatic aberration in color and NIR [1]

Color

NIR

[1] Z. Sadeghipoor, Y. M Lu, E. Mendez, and S. Süsstrunk, “Multiscale guided deblurring: Chromatic aberration correction in color and near-infrared imaging,” in 23rd European Signal Processing Conference (EUSIPCO), 2015, pp. 2336–2340.

Borrowing from spectral neighbors

Main idea: $$\nabla N \approx \nabla Color$$

Solution:

$$k = argmin_k ||\nabla N_{blur} - k * \nabla Y||_2^2$$

uniform blur
model assumption

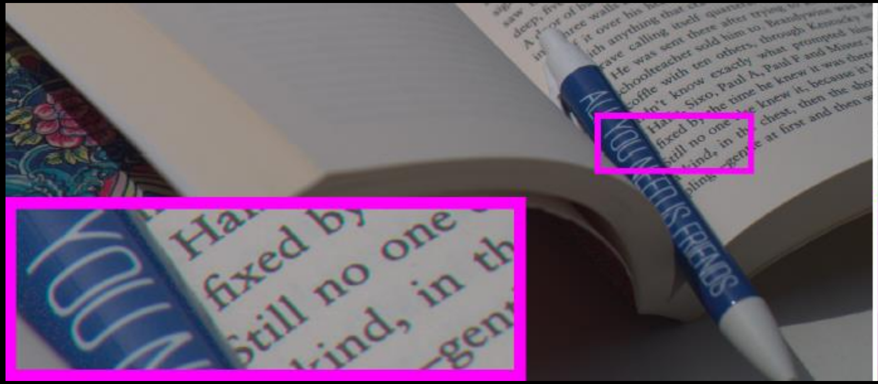
where k is a Gaussian kernel

$$N_{deblur} = argmin_N ||N_{blur} - k * N||_2^2 + ||\nabla N - \nabla Y||_2^2$$

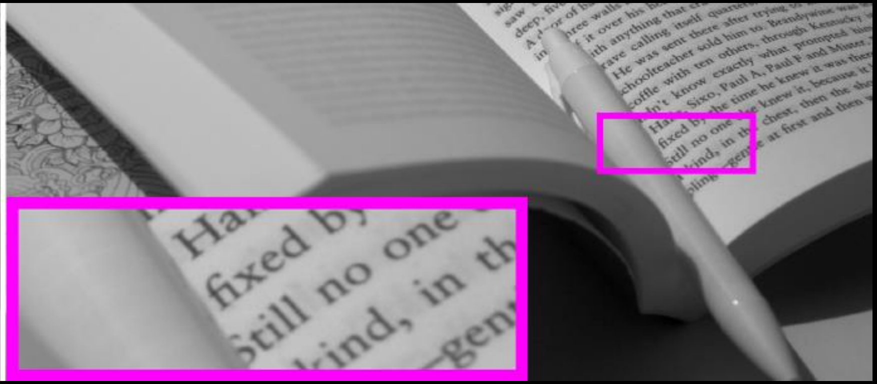
where Y is the pixel-wise color average

N_{blur}	original NIR
N_{deblur}	deblurred NIR

Shortcoming and solution



Color



NIR

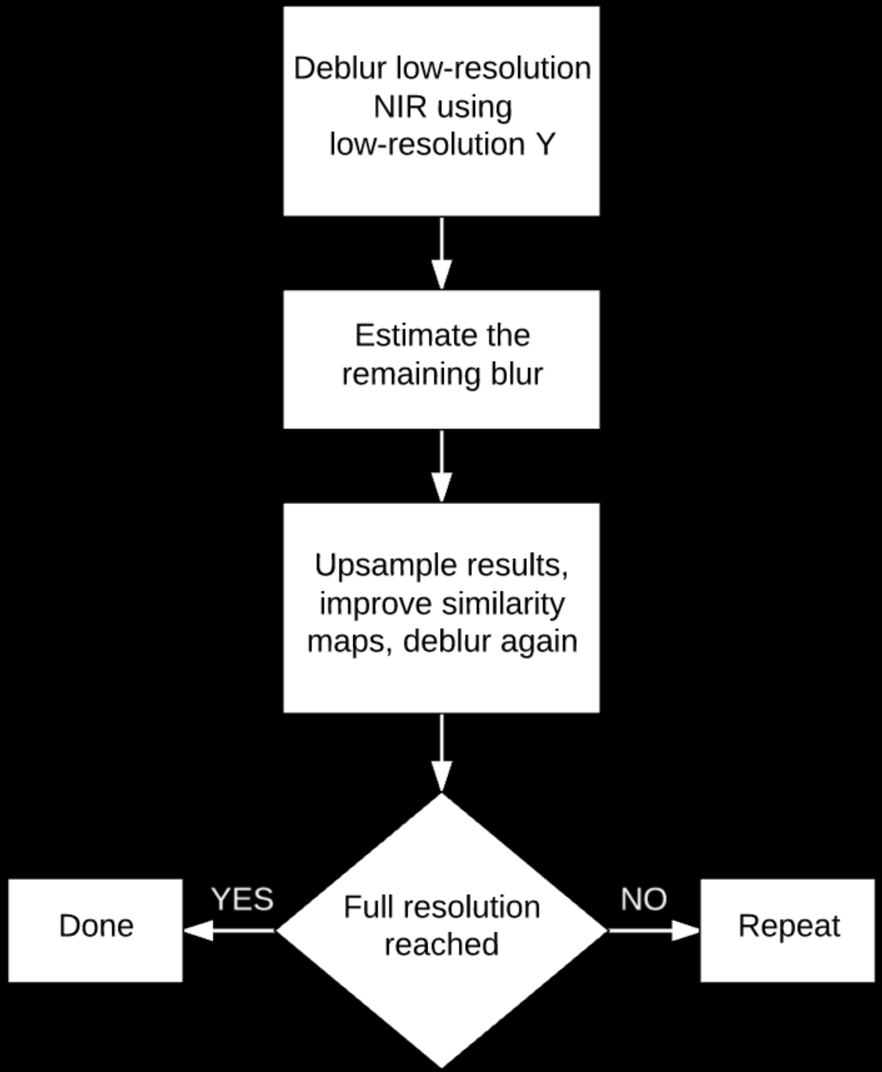
Color and NIR similarity:

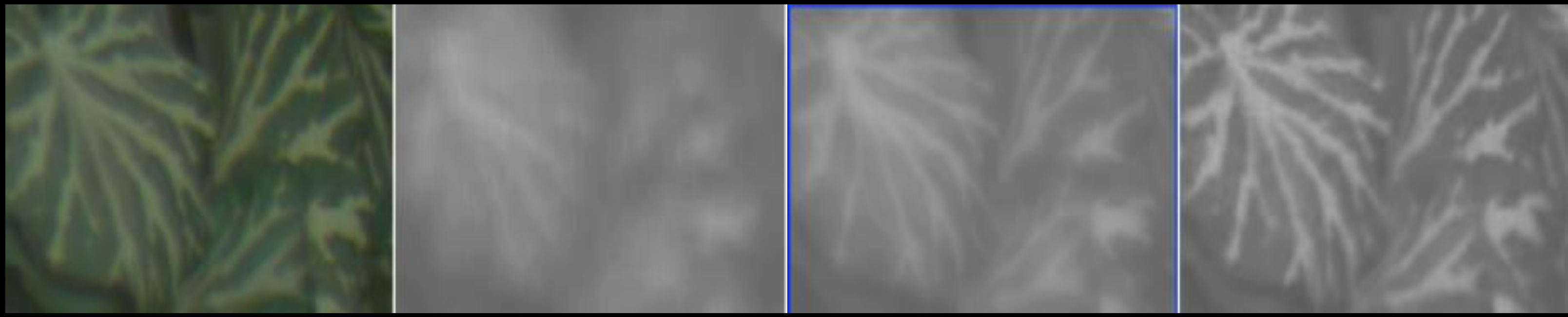
$$M = 1 - \frac{|\nabla N - \nabla(k * Y)|}{|\nabla N + \nabla(k * Y)|}$$

Similarity maps incorporated:

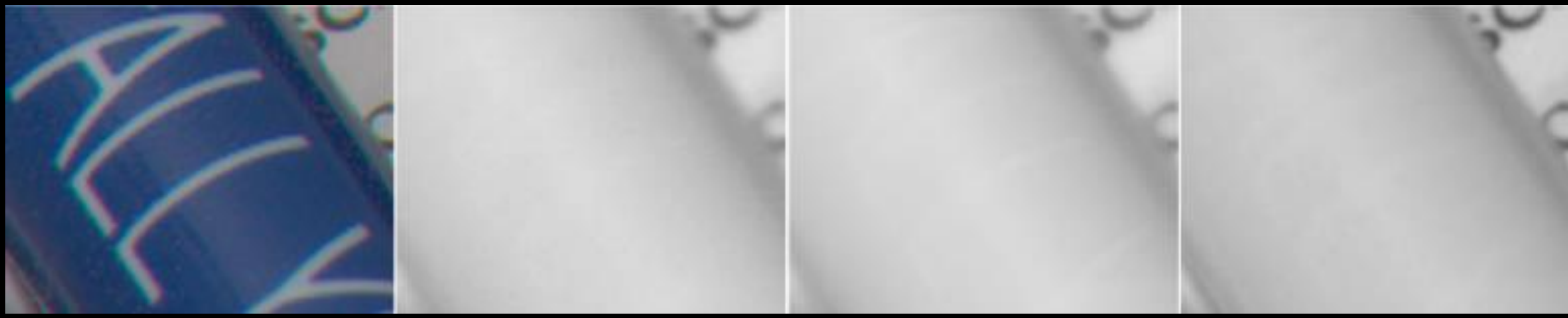
$$N_{deblur} = argmin_N \lambda ||N_{blur} - k * N||_2^2 + ||\nabla N - \mathbf{M} \odot \nabla Y||_2^2$$

Full deblurring algorithm



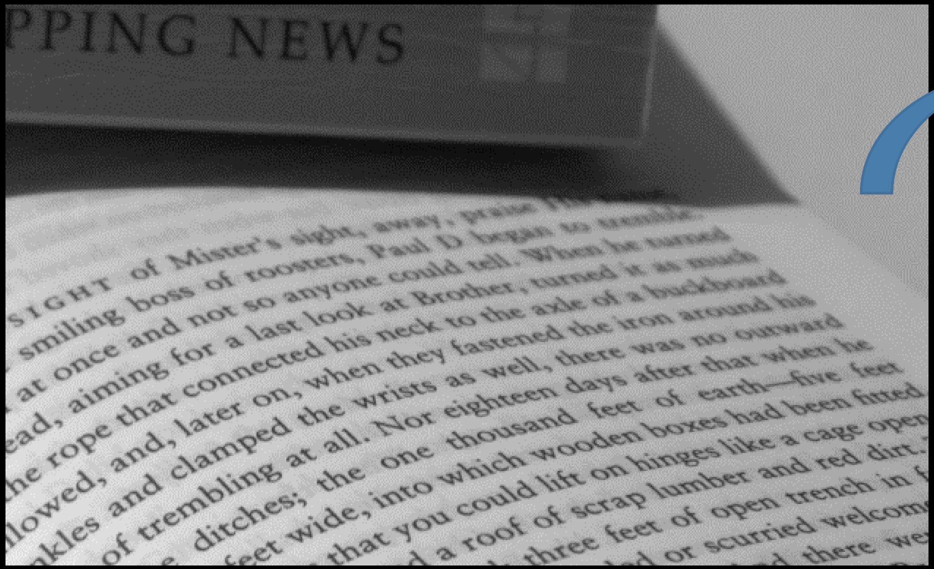


original RGB image | original blurred NIR | deblurring result | ground-truth NIR

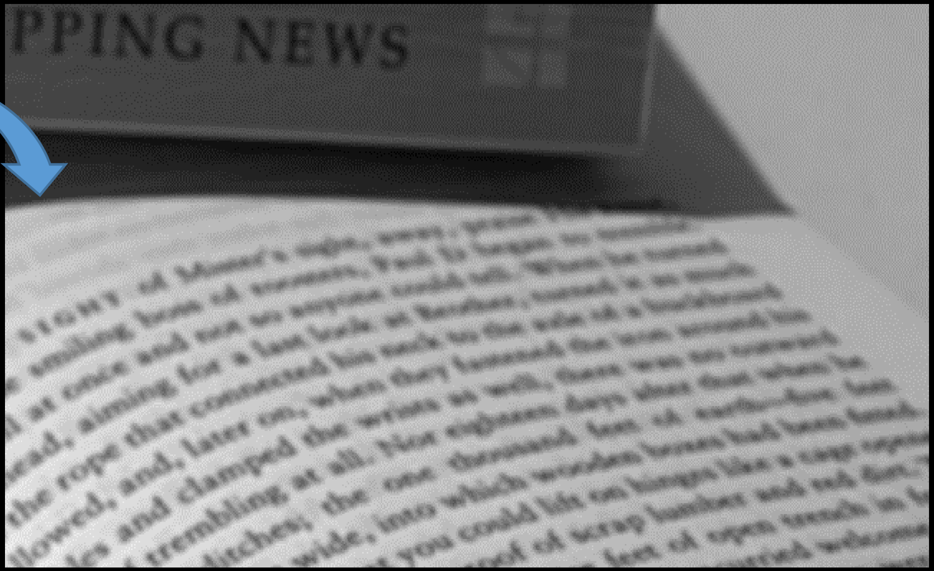


original RGB image | original blurred NIR | deblurring result | ground-truth NIR

Limitations: uniform blur assumption



Deblurring



Original NIR image

NIR image after deblurring

Limitations: color average as guide

Average sharpness values of different channels.

	R	G	B	Y
sharp.	0.6235	0.5942	0.6196	**0.5114**

→ Loss in hyperspectral information

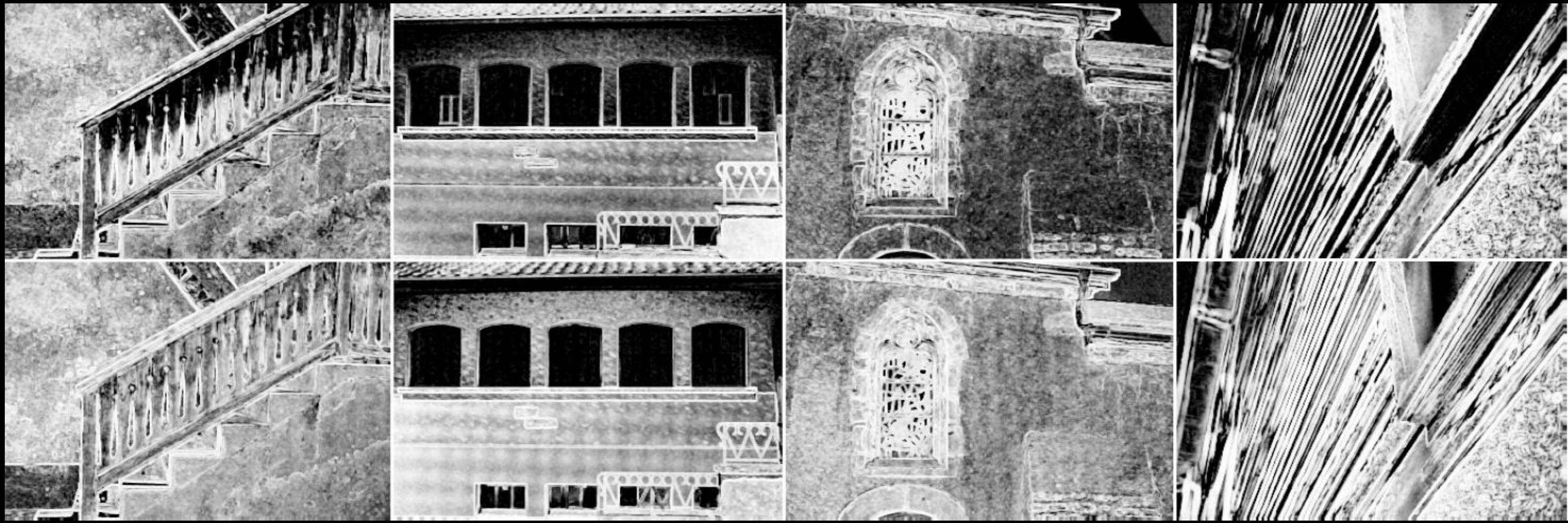
Searching for all information

Spectral correlation

	NIR	R	G	B
NIR	1	0.8436	0.7938	0.6975
R	-	1	0.9215	0.8510
G	-	-	1	0.9310
B	-	-	-	1

Spectrally closer
→ higher average NCC

Spectral correlation seen spatially



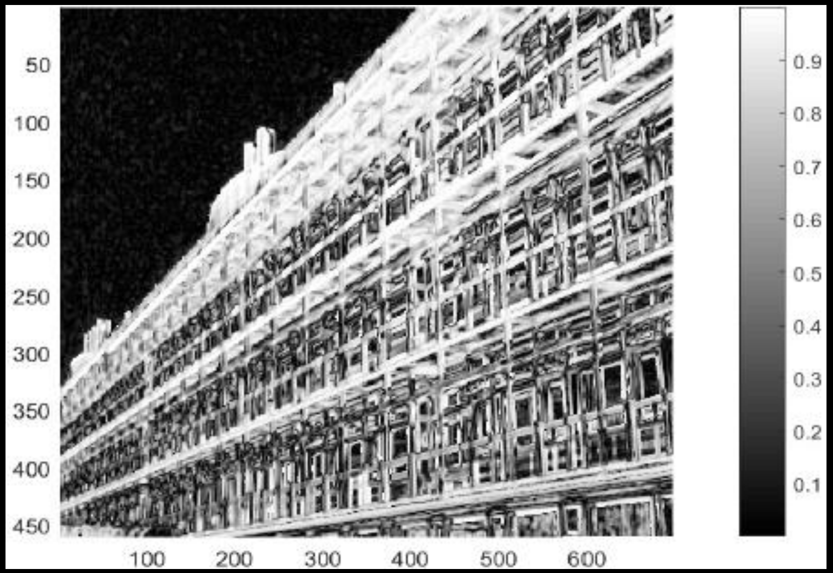
Top row: NCC between NIR and Blue
Bottom row: NCC between NIR and Red

Searching for all information

Spatial correlation

Luminance

NIR



NCC

High-frequency correlation

Searching for all information

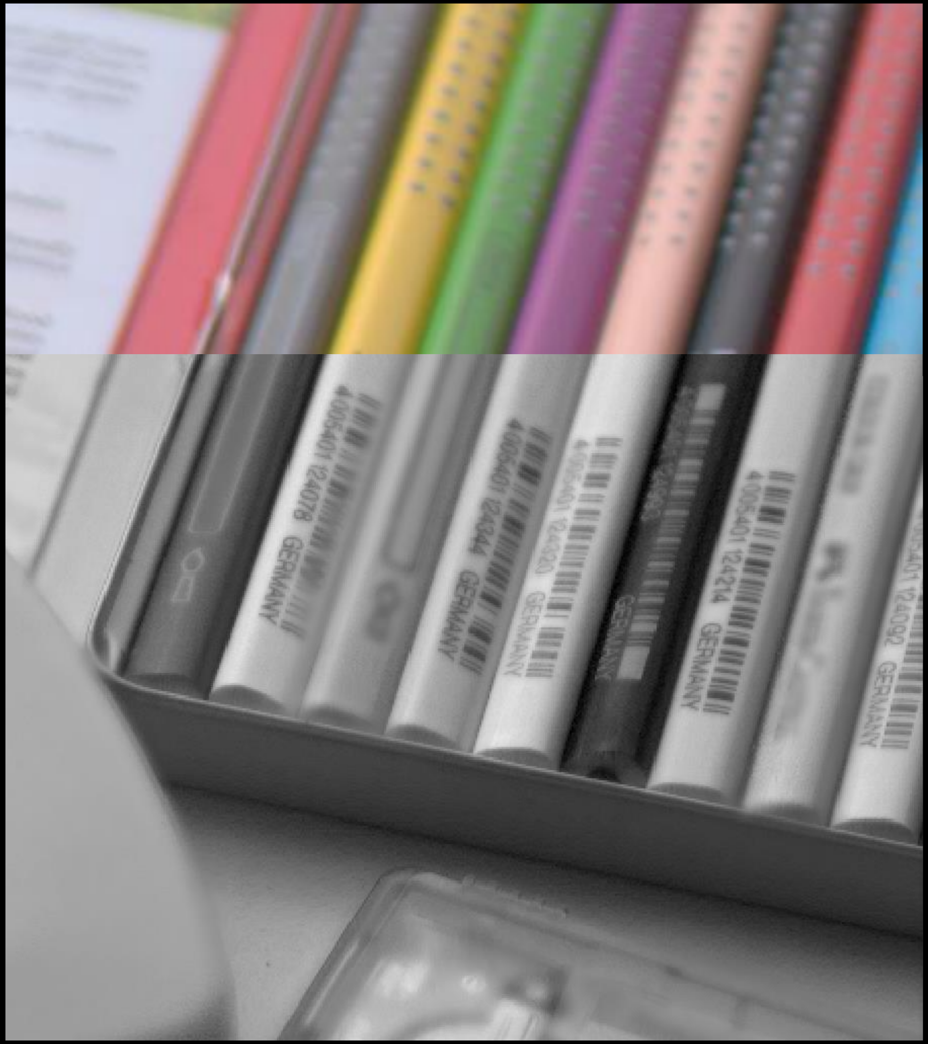
…but spatial distribution of high-frequency is
affected by object reflectance & chromatic aberration

Red

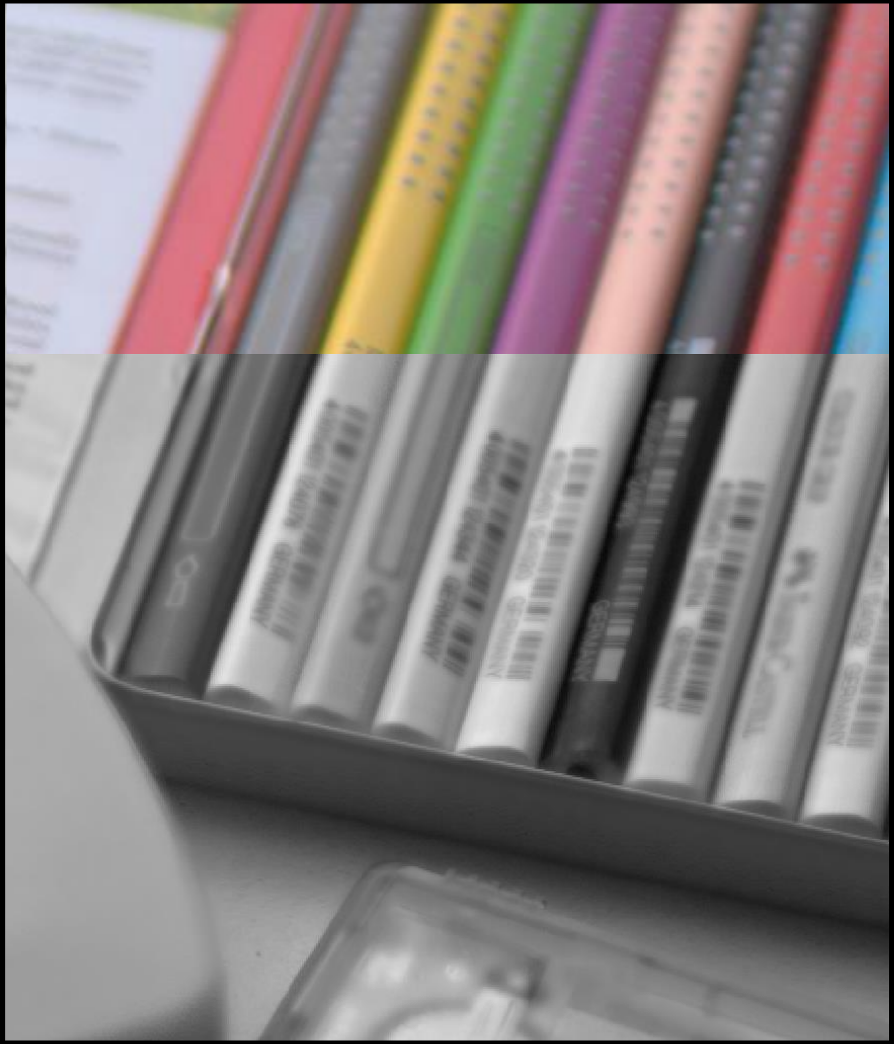
Green

Gradient difference

An example of spectral correlations

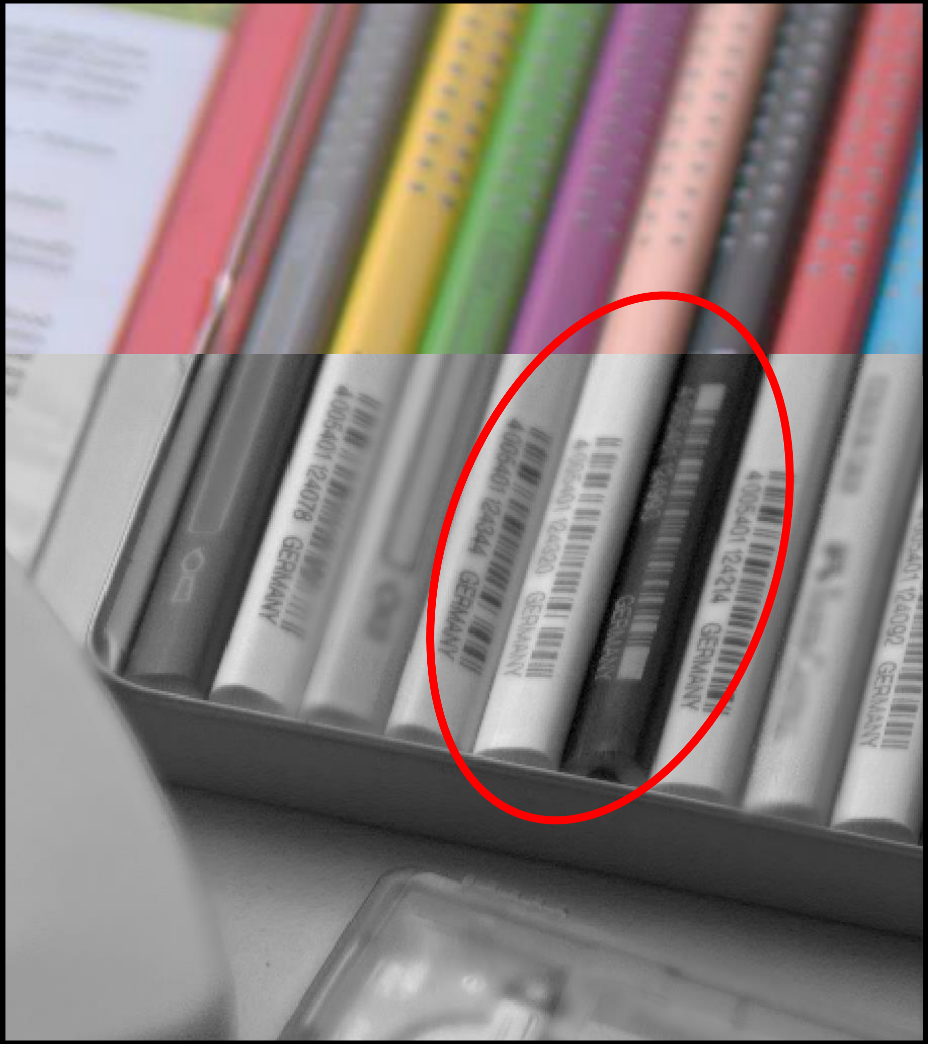


NIR deblurred from R channel

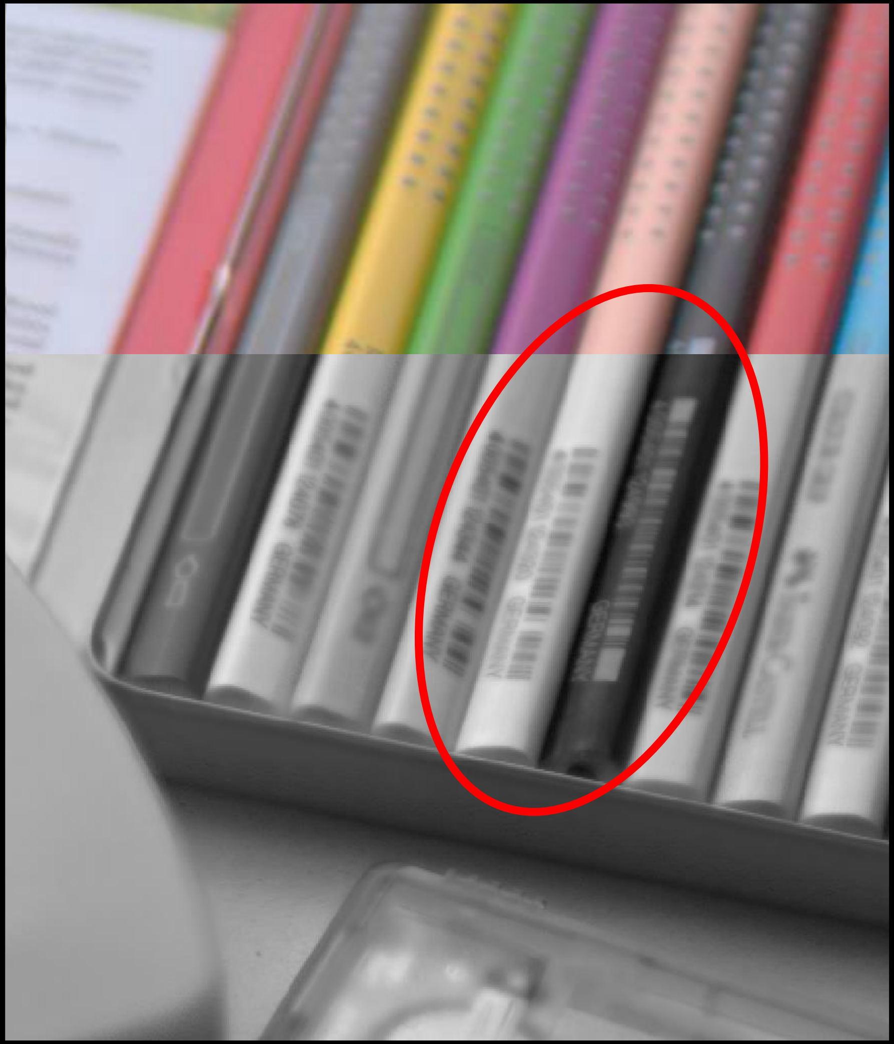


NIR deblurred from Y channel

An example of spectral correlations

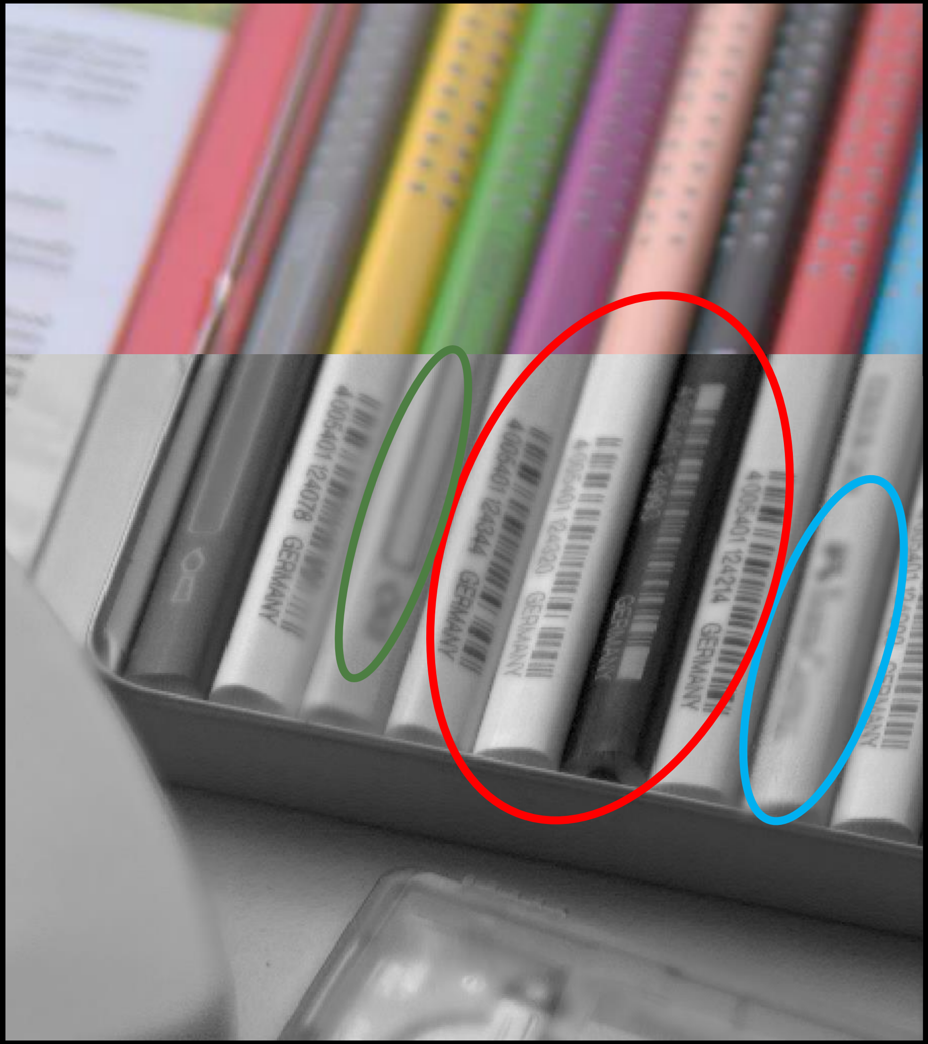


NIR deblurred from R channel

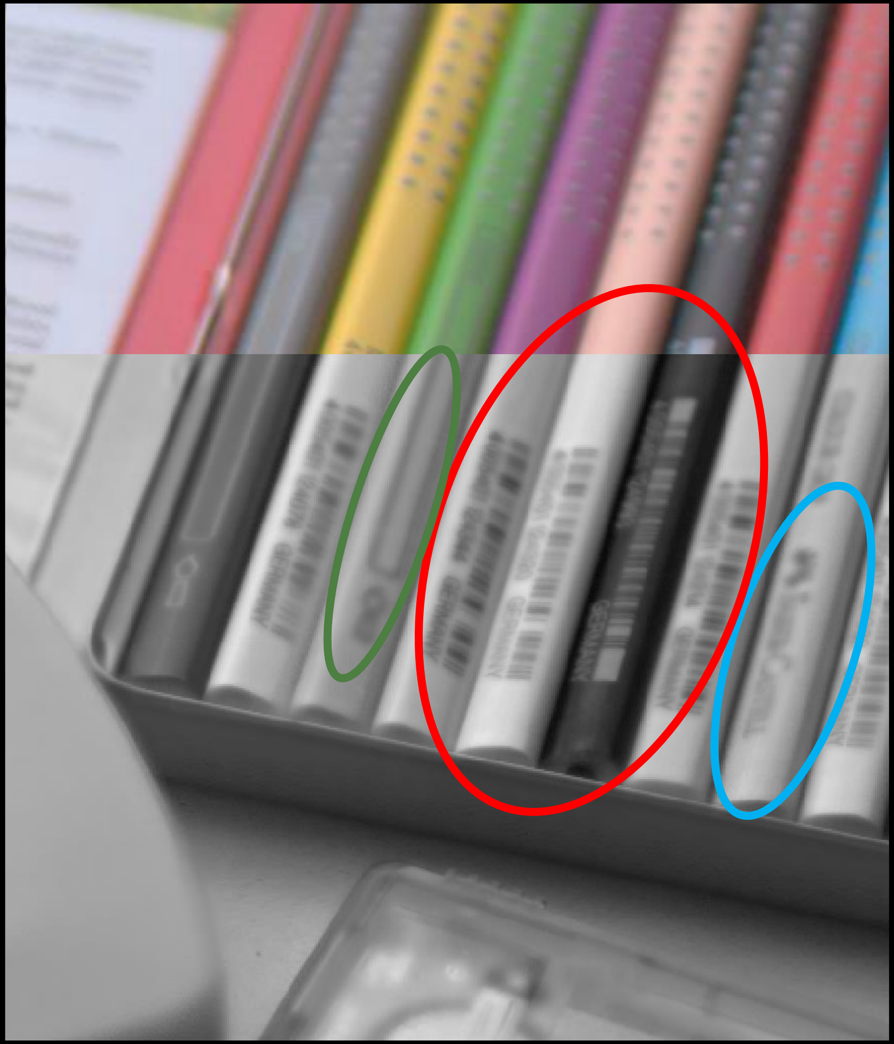


NIR deblurred from Y channel

An example of spectral correlations



NIR deblurred from R channel



NIR deblurred from Y channel

Objective

Leverage spectral-spatial correlations,
making use of the best information for deblurring

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Leverage spectral-spatial correlations,

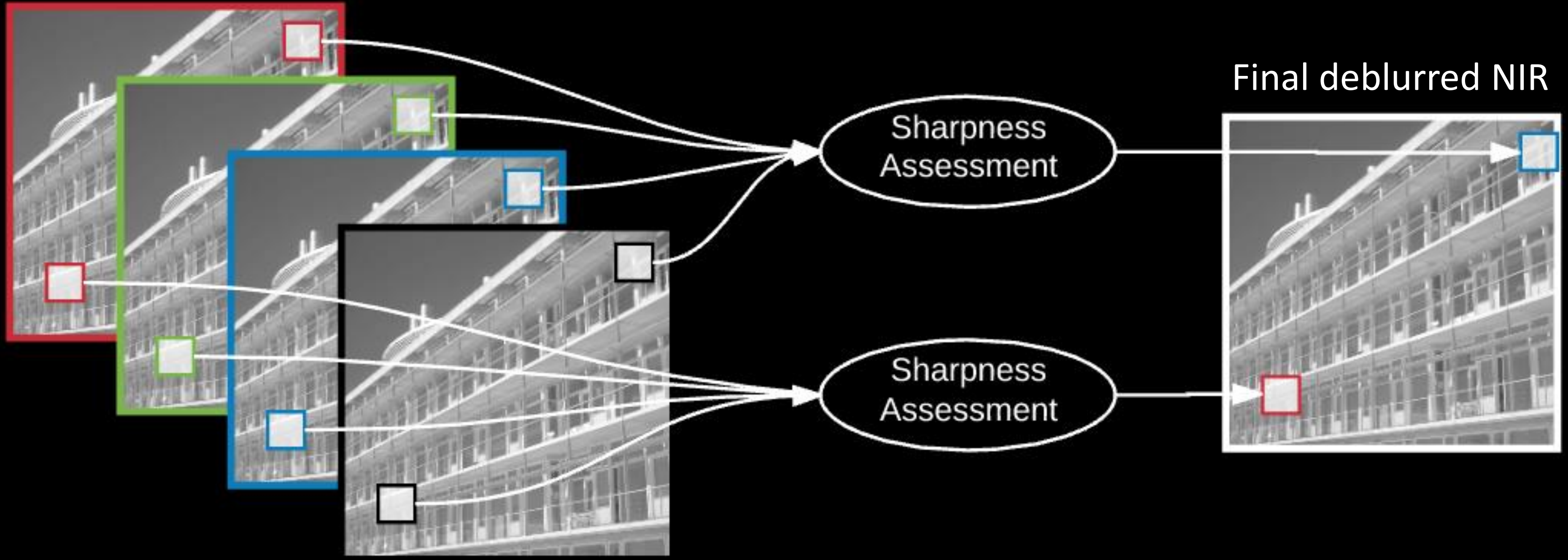
making use of the best information for deblurring

Constraint: no *apriori* knowledge on what spectral information is the most relevant for every spatial location

Combine advantages of each channel

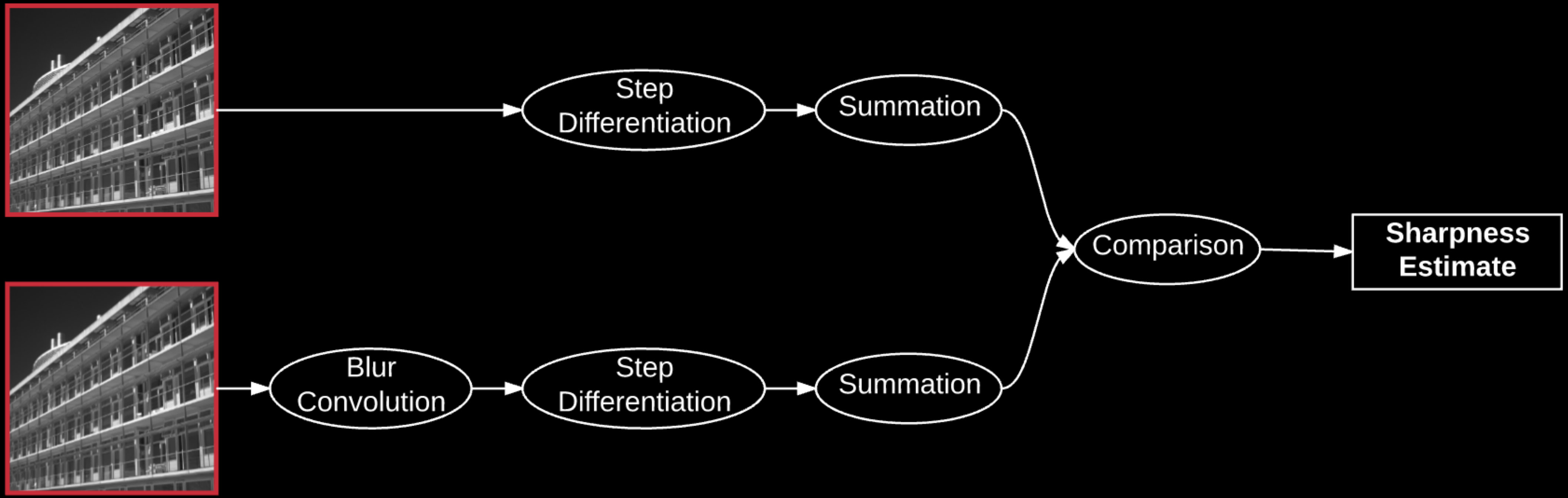
NIR deblurred based
on R G and B channels

Final deblurred NIR



Original out-of-focus NIR

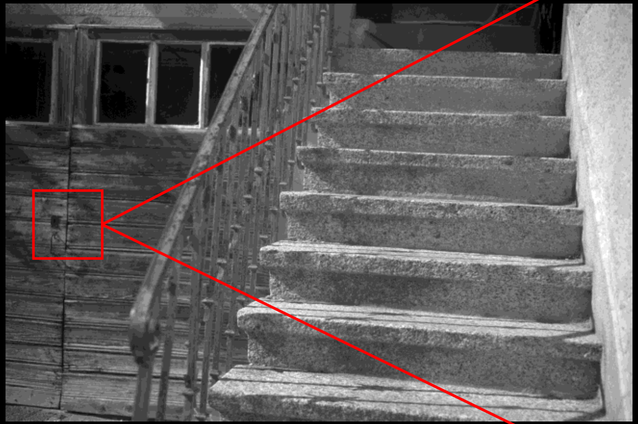
Sharpness assessment [2]



[2] F. Crete, et al. "The blur effect: perception and estimation with a new no-reference perceptual blur metric." *International Society for Optics and Photonics*, 2007.

Deblurring results

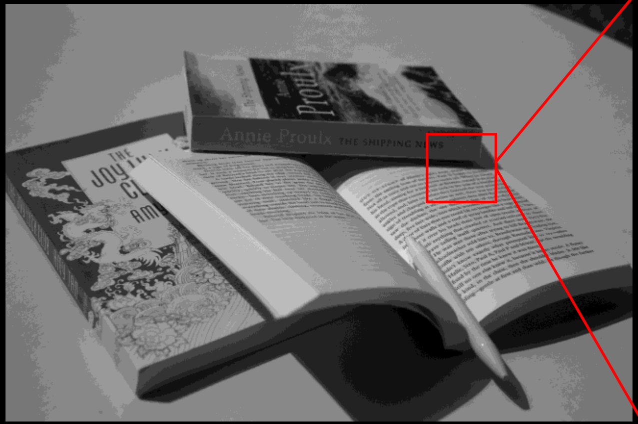
State of the art [1]:

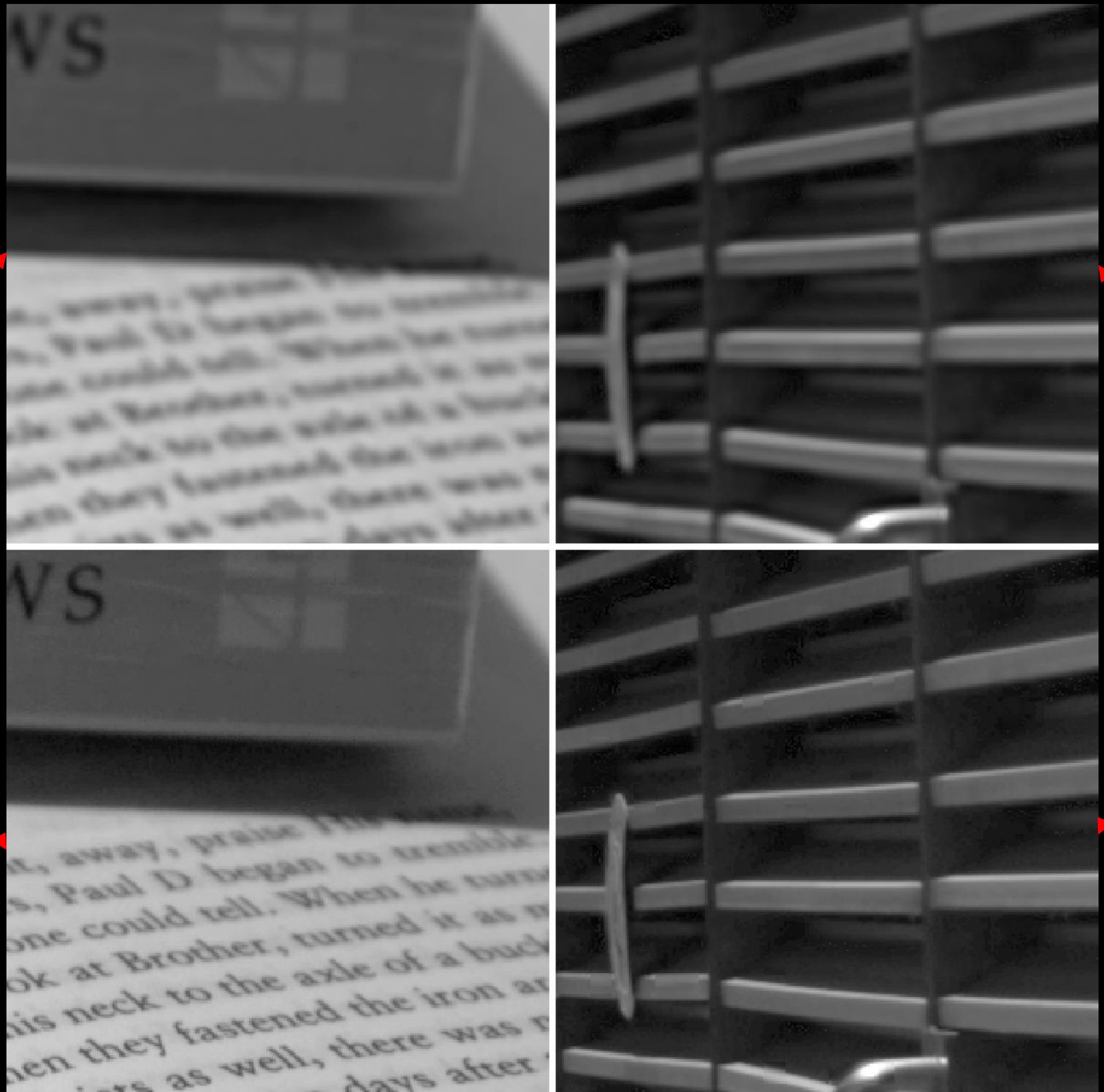


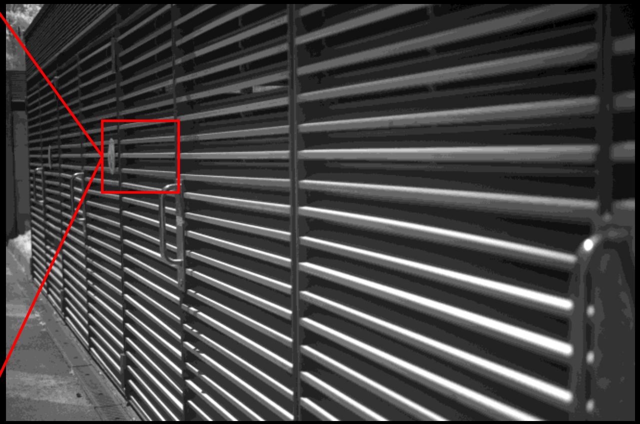
Ours:

Deblurring results

State of the art [1]:

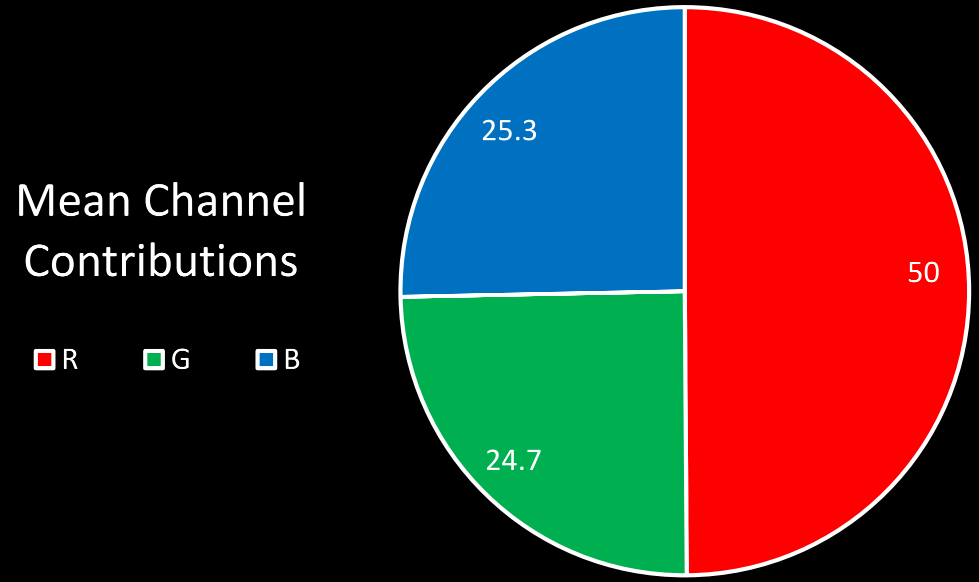






Ours:

Recombining from RGB



Simpler is better: any band combination loses high-frequency

Conclusion

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- 48.8% increase in sharpness (Crete)

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- Increased depth of field

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- 48.8% increase in sharpness (Crete)
- Increased depth of field
- Due to chromatic aberration and reflectance properties, spectral averaging causes a spatial low-pass filtering

Thank you for your attention

Q&A

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Let F be the luminance component of an image or a video frame of size of $m \times n$ pixels. To estimate the blur annoyance of F the first step consists in blurred it in order to obtain a blurred image B. We choose an horizontal and a vertical strong low-pass filter (1) to model the blur effect and to create B_{Ver} and B_{Hor}.

$$h_v = \frac{1}{9} \times [1\,1\,1\,1\,1\,1\,1\,1\,1] \qquad h_h = transpose(h_v) = h_v' \tag{1}$$

$$B_{Ver} = h_v * F \qquad B_{Hor} = h_h * F$$

Then, in order to study the variations of the neighboring pixels, we compute the absolute difference images D_F_{Ver}, D_F_{Hor}, D_B_{Ver} and D_B_{Hor} as followed:

$$D\_F_{Ver}(i,j) = Abs(F(i,j) - F(i-1,j)) \ \ for\ i=1\ to\ m-1,\ \ j=0\ to\ n-1$$
$$D\_F_{Hor}(i,j) = Abs(F(i,j) - F(i,j-1)) \ \ for\ j=1\ to\ n-1,\ \ i=0\ to\ m-1$$
$$D\_B_{Ver}(i,j) = Abs(B_{Ver}(i,j) - B_{Ver}(i-1,j)) \ \ for\ i=1\ to\ m-1,\ \ j=0\ to\ n-1$$
$$D\_B_{Hor}(i,j) = Abs(B_{Hor}(i,j) - B_{Hor}(i,j-1)) \ \ for\ j=1\ to\ n-1,\ \ i=0\ to\ m-1$$

As we explain in the previous subsection, we need to analyze the variation of the neighboring pixels after the blurring step. If this variation is high, the initial image or frame was sharp whereas if the variation is slight, the initial image or frame was already blur. This variation is evaluated only on the absolute differences which have decreased:

$$V_{Ver} = Max(0, D\_F_{Ver}(i,j) - D\_B_{Ver}(i,j)) \ \ for\ i=1\ to\ m-1,\ \ j=1\ to\ n-1$$
$$V_{Hor} = Max(0, D\_F_{Hor}(i,j) - D\_B_{Hor}(i,j)) \ \ for\ i=1\ to\ m-1,\ \ j=1\ to\ n-1 \tag{3}$$

Then, in order to compare the variations from the initial picture, we compute the sum of the coefficients of D_F_{Ver} , D_F_{Hor}, D_V_{Ver}, D_V_{Hor} as followed:

$$s\_F_{Ver} = \sum_{i,j=1}^{m-1,n-1} D\_F_{Ver}(i,j) \qquad s\_F_{Hor} = \sum_{i,j=1}^{m-1,n-1} D\_F_{Hor}(i,j)$$
$$s\_V_{Ver} = \sum_{i,j=1}^{m-1,n-1} D\_V_{Ver}(i,j) \qquad s\_V_{Hor} = \sum_{i,j=1}^{m-1,n-1} D\_V_{Hor}(i,j) \tag{4}$$

Finally, we have to normalize the result in a defined range from 0 to 1:

$$b\_F_{Ver} = \frac{s\_F_{Ver} - s\_V_{Ver}}{s\_F_{Ver}} \qquad b\_F_{Hor} = \frac{s\_F_{Hor} - s\_V_{Hor}}{s\_F_{Hor}} \tag{5}$$

We note that the variations between the two differences images D_F and D_B are always slighter than the values of the initial difference image D_F.

Then, we select the blur the more annoying among the vertical one and the horizontal one as the final blur value.

$$blur_F = Max(b\_F_{Ver}, b\_F_{Hor}) \tag{6}$$

Deblurring Algorithm

after a deblurring iteration, there is some blur still left
(call it residual blur)

$$\mathcal{N}_d^{(p)} = k_{\text{res}}^{(p)} * \mathcal{N}^{(p)}.$$

We estimate the residual kernel, $k_{\text{res}}^{(p)}$, by solving:

$$k_{\text{res}}^{(p)} = f(\mathcal{N}_d^{(p)}, Y^{(p)}).$$

$$k^{(0)} = f(\mathcal{N}_b^{(0)}, Y^{(0)}) \triangleq \underset{k}{\operatorname{argmin}} \|\nabla \mathcal{N}_b^{(0)} - k * \nabla Y^{(0)}\|_F^2$$
$$\text{s.t. } k(m,n) = \frac{1}{c}\exp\left(-\frac{m^2+n^2}{2\sigma^2}\right).$$

use it to find a blurry Y to compare it
to the new deblurred NIR and improve M

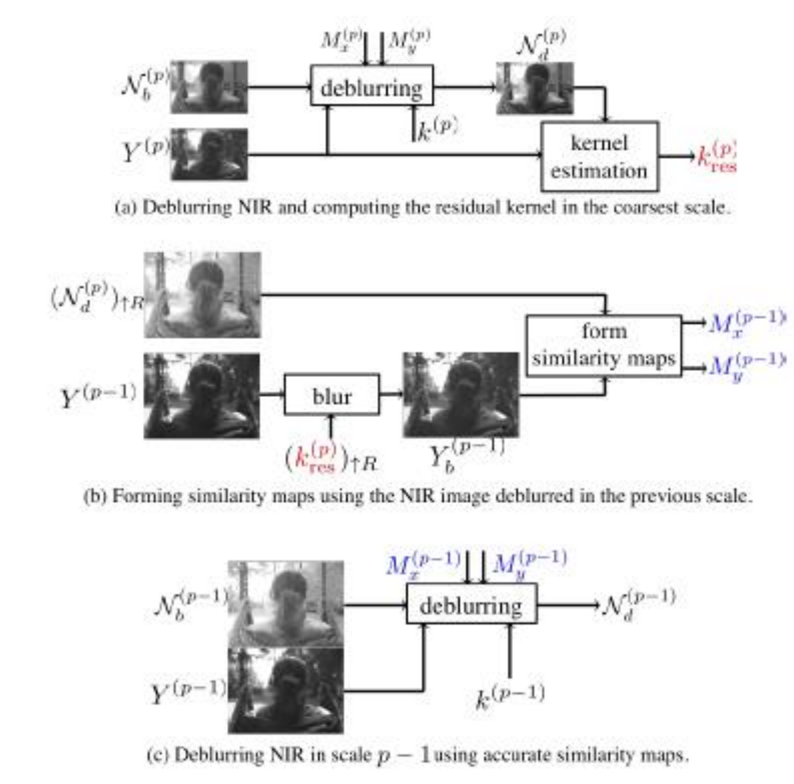
$$Y_b^{(p-1)} = (k_{\text{res}}^{(p)})_{\uparrow R} * Y^{(p-1)}.$$

$$\begin{aligned}\mathcal{N}_d^{(p)} &= g(\mathcal{N}_b^{(p)}, Y^{(p)}, M_x^{(p)}, M_y^{(p)}) \\ &\triangleq \underset{\mathcal{N}^{(p)}}{\operatorname{argmin}} \lambda \|\mathcal{N}_b^{(p)} - k^{(p)} * \mathcal{N}^{(p)}\|_F^2 \\ &\quad + \sum_{l \in \{x,y\}} \|\nabla_l \mathcal{N}^{(p)} - M_l^{(p)} \odot \nabla_l Y^{(p)}\|_F^2\end{aligned}$$

$$M_l^{(p-1)} = 1 - \frac{|\nabla_l (\mathcal{N}_d^{(p)})_{\uparrow R} - \nabla_l Y_b^{(p-1)}|}{|\nabla_l (\mathcal{N}_d^{(p)})_{\uparrow R} + \nabla_l Y_b^{(p-1)}|}, l \in \{x, y\},$$

use it to find a blurry Y to compare it
to the new deblurred NIR and improve M

$$\mathcal{N}_d^{(p-1)} = g(\mathcal{N}_b^{(p-1)}, Y^{(p-1)}, M_x^{(p-1)}, M_y^{(p-1)}),$$



(a) Deblurring NIR and computing the residual kernel in the coarsest scale.
(b) Forming similarity maps using the NIR image deblurred in the previous scale.
(c) Deblurring NIR in scale $p-1$ using accurate similarity maps.

Deblurring Optimization

$$N_d^{(p)} = \underset{N^{(p)}}{\operatorname{argmin}} \; \lambda \| N_b^{(p)} - k^{(p)} * N^{(p)} \|_2^2 + \| \nabla_x N^{(p)} - M_x^{(p)} \odot \nabla_x Y^{(p)} \|_2^2 + \| \nabla_y N^{(p)} - M_y^{(p)} \odot \nabla_y Y^{(p)} \|_2^2$$

$$= \underset{N^{(p)}}{\operatorname{argmin}} \; \lambda \| n_b^{(p)} - K^{(p)} n^{(p)} \|_2^2 + \| F_1 n^{(p)} - y_1^{(p)} \|_2^2 + \| F_2 n^{(p)} - y_2^{(p)} \|_2^2 \qquad \left[y_i^{(p)} = M_i^{(p)} \odot \nabla_i Y^{(p)} \right]$$

$$\frac{\nabla J(n)}{\nabla n} = 2\lambda K^{(p)T} \left(K^{(p)} n^{(p)} - n_b^{(p)} \right) + 2F_1^T \left(F_1 n^{(p)} - y_1^{(p)} \right) + 2F_2^T \left(F_2 n^{(p)} - y_2^{(p)} \right)$$

Affine fit of L^2-norms squared $\rightarrow$ convex & optimal $n_d^{(p)}$ at $\frac{\nabla J(n)}{\nabla n} = 0$

$$2\lambda K^T K n_d - 2\lambda K^T n_b + 2F_1^T F_1 n_d - 2F_1^T y_1 + 2F_2^T F_2 n_d - 2F_2^T y_2 = 0$$

$$\left(2\lambda K^T K + 2F_1^T F_1 + 2F_2^T F_2 \right) n_d = 2\lambda K^T n_b + 2F_1^T y_1 + 2F_2^T y_2$$

$$A = \lambda K^T K + F_1^T F_1 + F_2^T F_2$$
$$\mathbf{b} = \lambda K^T n_b + F_1^T y_1 + F_2^T y_2$$

Size: $LP \times LP$, $LP \times 1$ } For $L \times P$ images

$$A n_d = b$$

A is real & symm. $\Rightarrow$ hermitian so we have: $A = S \Lambda' S^{-1}$

$$S \Lambda' S^{-1} n_d = b$$
$$\Lambda' S^{-1} n_d = S^{-1} b$$

If A is circulant then we have: $F^{-1} \Lambda F n_d = b$, $\Lambda F n_d = F b$ where F is the LP-length DFT matrix

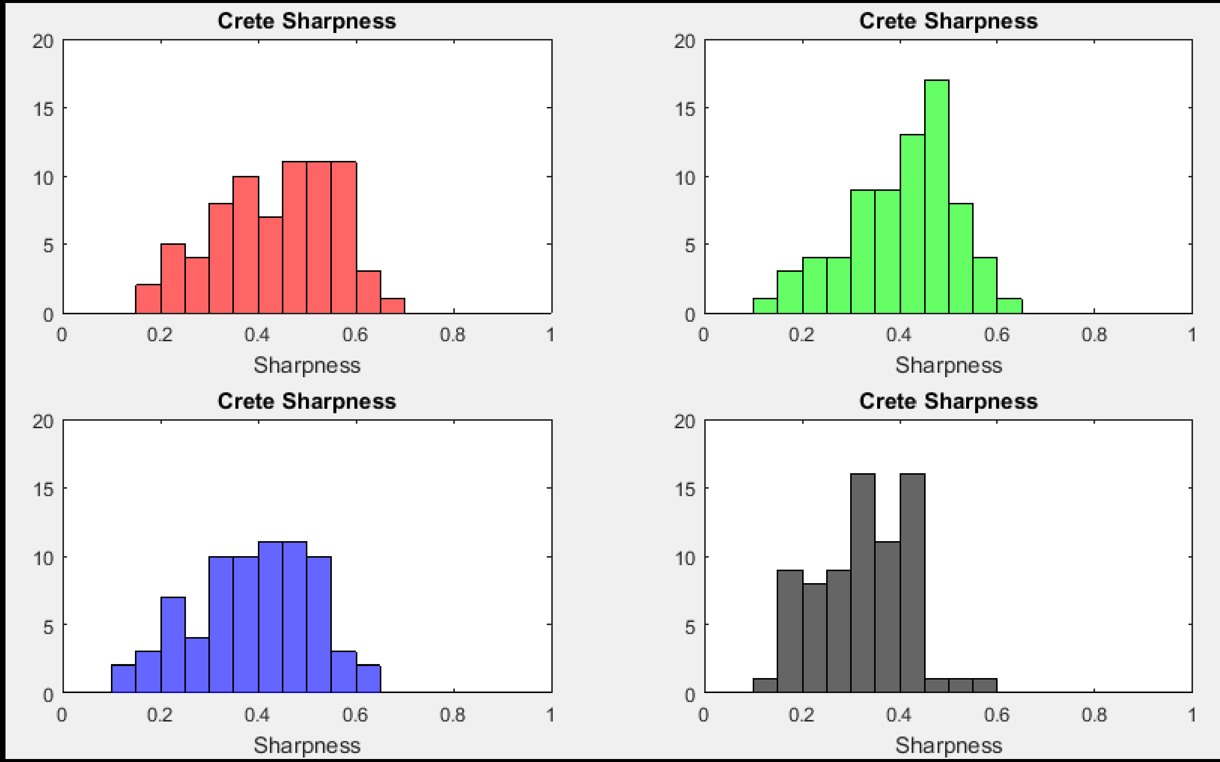
$\rightarrow \Lambda n_d(\omega) = b(\omega)$ & Λ diagonal

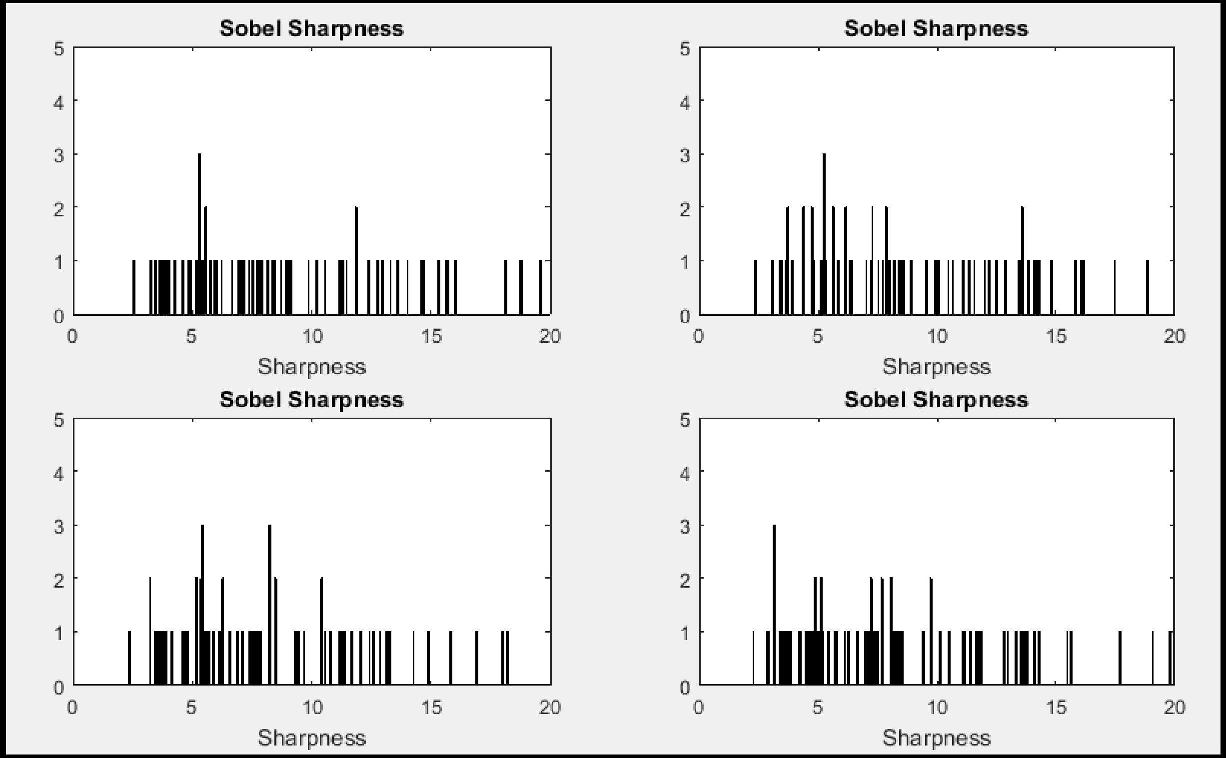
$\rightarrow n_d(\omega)$

$$r = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{\left(\sum_m \sum_n (A_{mn} - \bar{A})^2 \right) \left(\sum_m \sum_n (B_{mn} - \bar{B})^2 \right)}}$$

$$\begin{aligned} \mathcal{N}_d^{(p)} &= g(\mathcal{N}_b^{(p)}, Y^{(p)}, M_x^{(p)}, M_y^{(p)}) \\ &\triangleq \underset{\mathcal{N}^{(p)}}{\operatorname{argmin}} \, \lambda \| \mathcal{N}_b^{(p)} - k^{(p)} * \mathcal{N}^{(p)} \|_F^2 \\ &\quad + \sum_{l \in \{x,y\}} \| \nabla_l \mathcal{N}^{(p)} - M_l^{(p)} \odot \nabla_l Y^{(p)} \|_F^2 \end{aligned}$$

Validation on the Dataset





<u>Dataset average sharpness results:</u>

R-G-B-Y

0.4319-0.4044-0.3911-0.3253

<u>Dataset average sharpness results:</u>

R-G-B-Y

8.9360-8.7885-8.3071-8.3479

Recombined Results

Blur estimation:

- Elder and Zucker (1998)
- Hu and Haan (2006)
- Crete *et al.* (2007)

Improve on blur estimation from edges

State-of-the-art strategy:
re-blurring the images

J. Elder, and S. Zucker. "Local scale control for edge detection and blur estimation." *IEEE Transactions on Pattern Analysis and machine intelligence* 1998: 699-716.
H. Hu, and G. Haan. "Low cost robust blur estimator." *IEEE International Conference on Image Processing*, 2006.
F. Crete, et al. "The blur effect: perception and estimation with a new no-reference perceptual blur metric." *International Society for Optics and Photonics*, 2007.