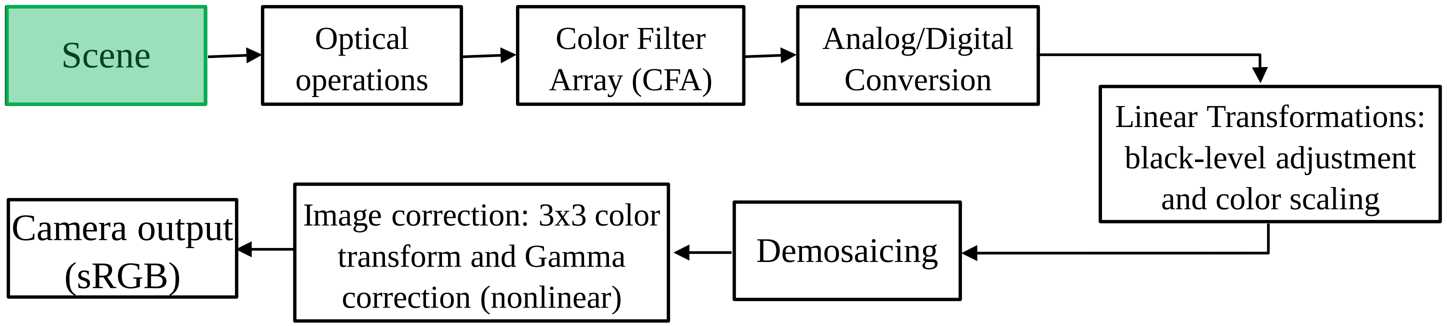
Pattern-independent Demosaicing;

Presented by Daniel Khashabi
Joint work with Sebastian Nowozin, Jeremy Jancsary, Andrew W. Fitzgibbon and Bruce Lindbloom

Outline

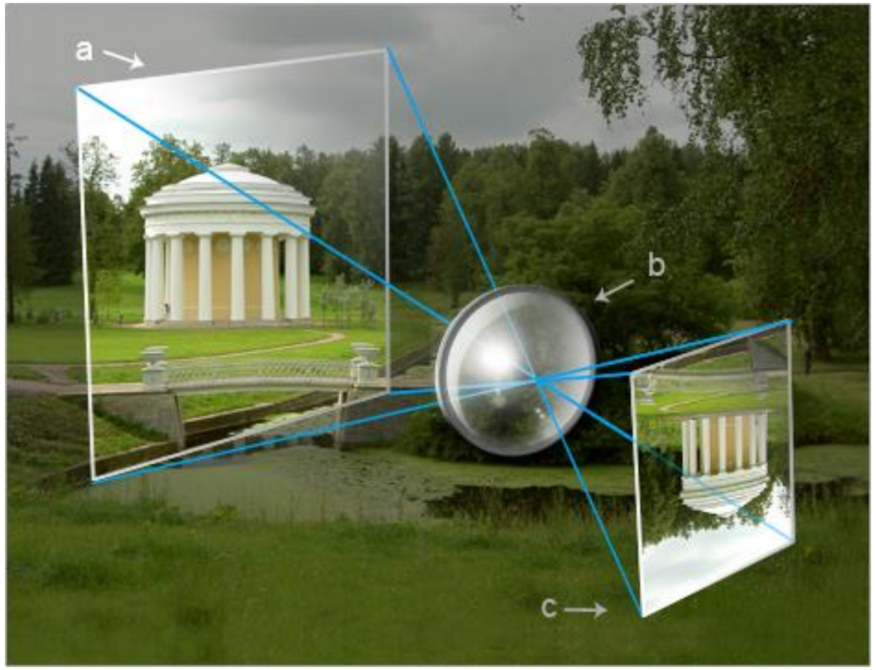
- Demosaicing problem
- Creating input-output pairs
- Our demosaicing model
- Experiments

A simple camera pipeline



A simple camera pipeline

Scene → Optical operations → Color Filter Array (CFA) → Analog/Digital Conversion → Linear Transformations: black-level adjustment and color scaling → Demosaicing → Image correction: 3x3 color transform and Gamma correction (nonlinear) → Camera output (sRGB)



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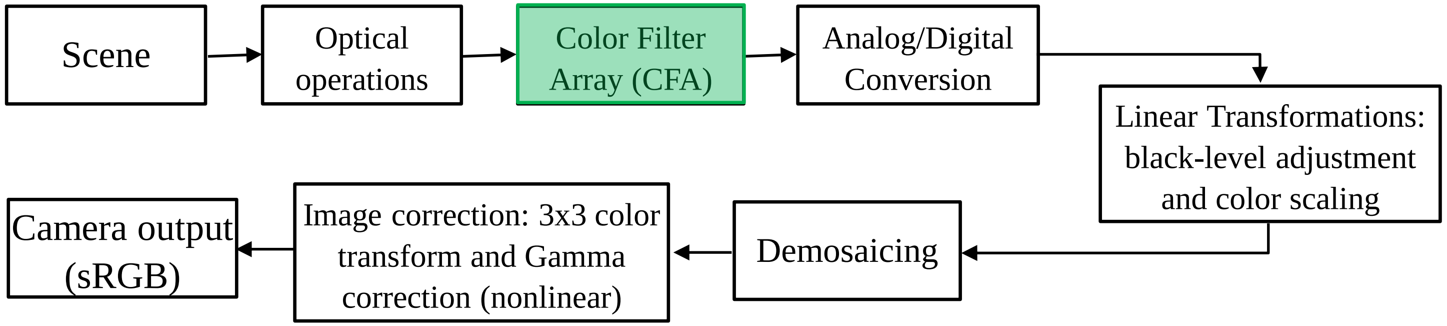

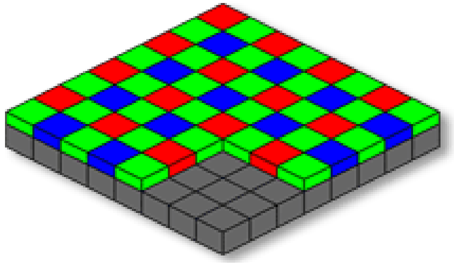

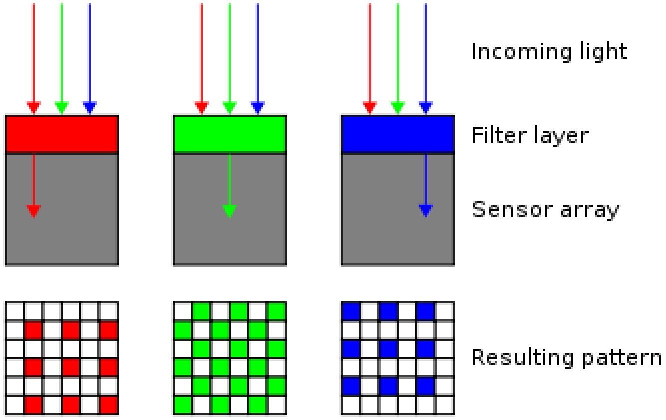

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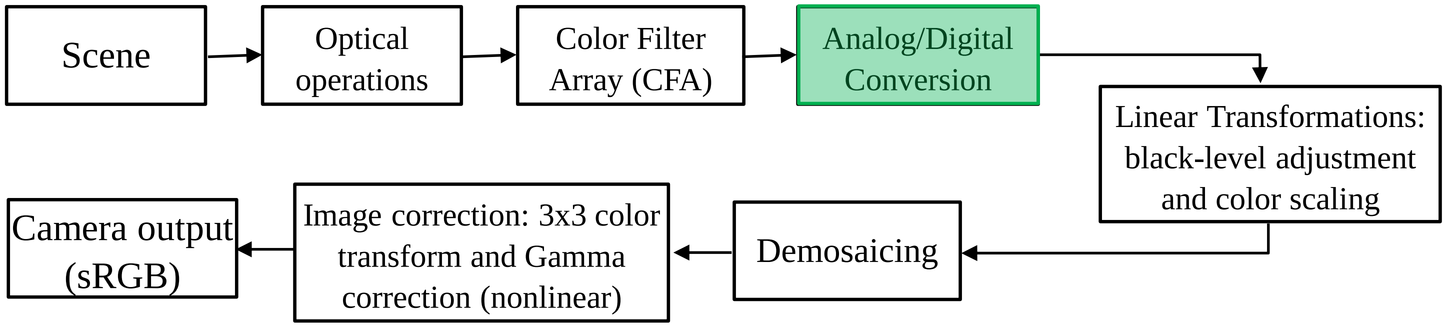

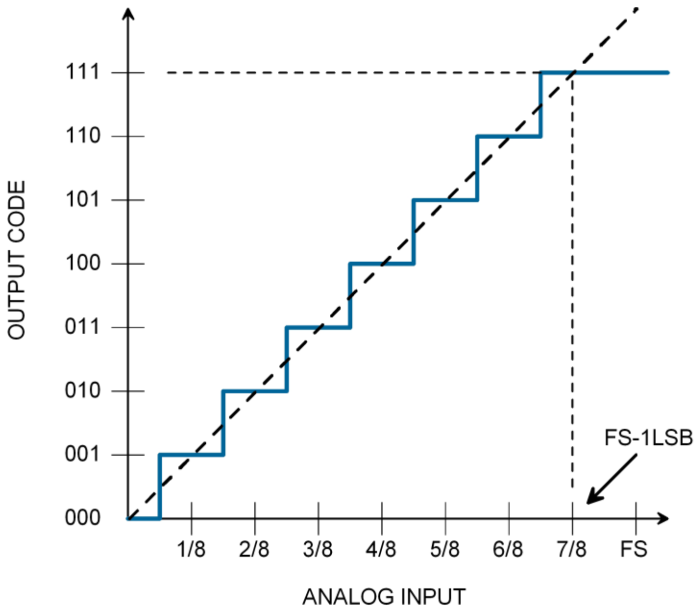

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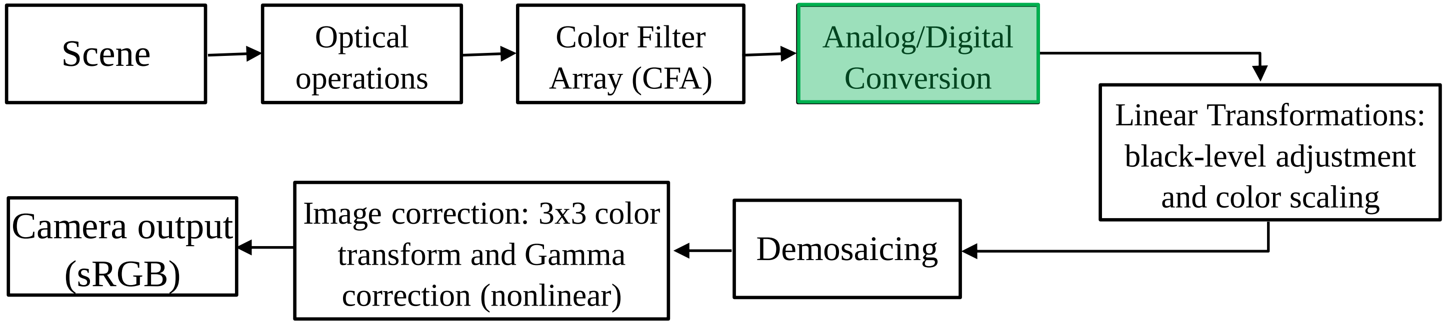

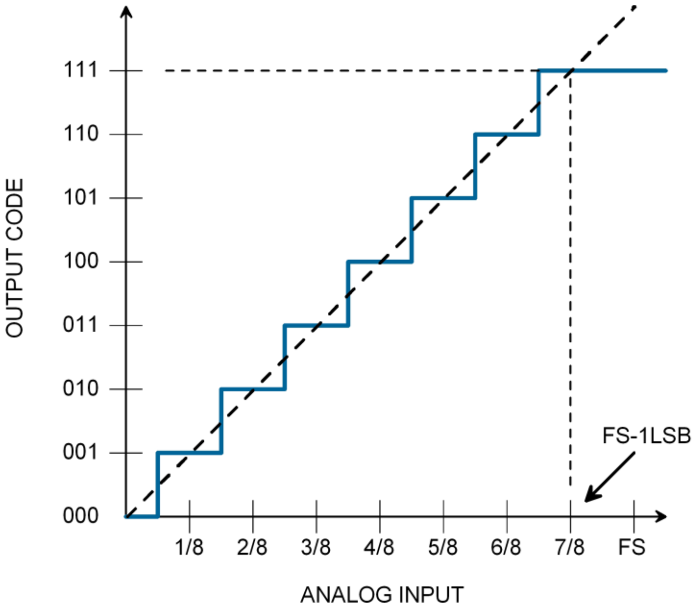

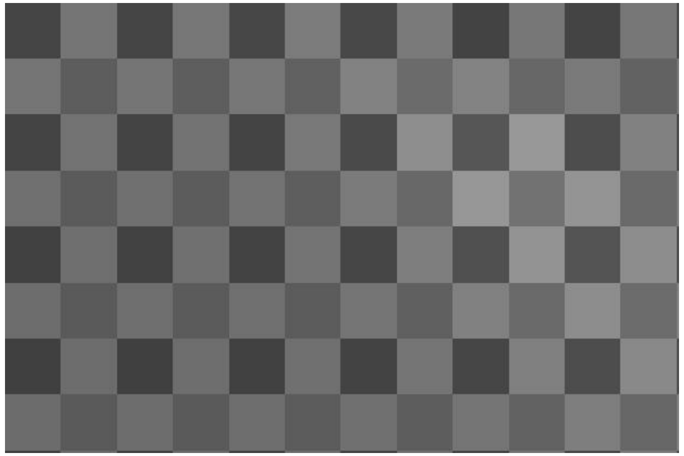

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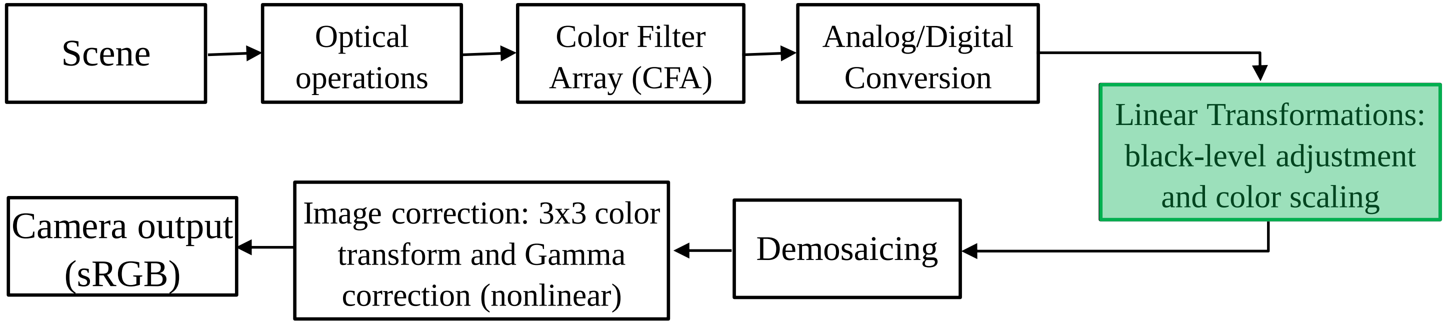

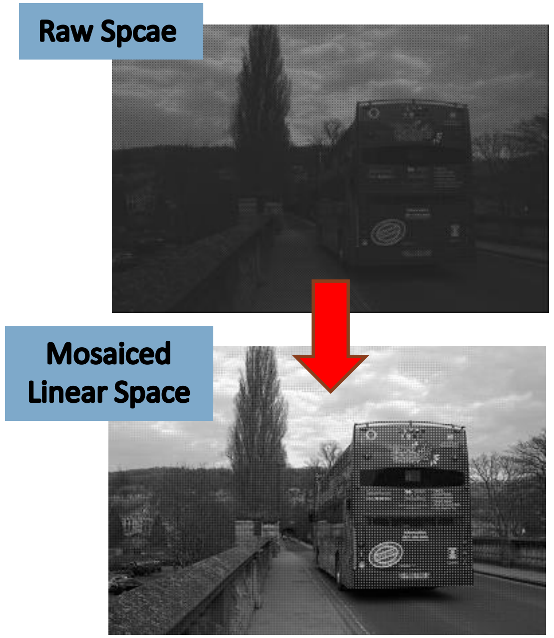

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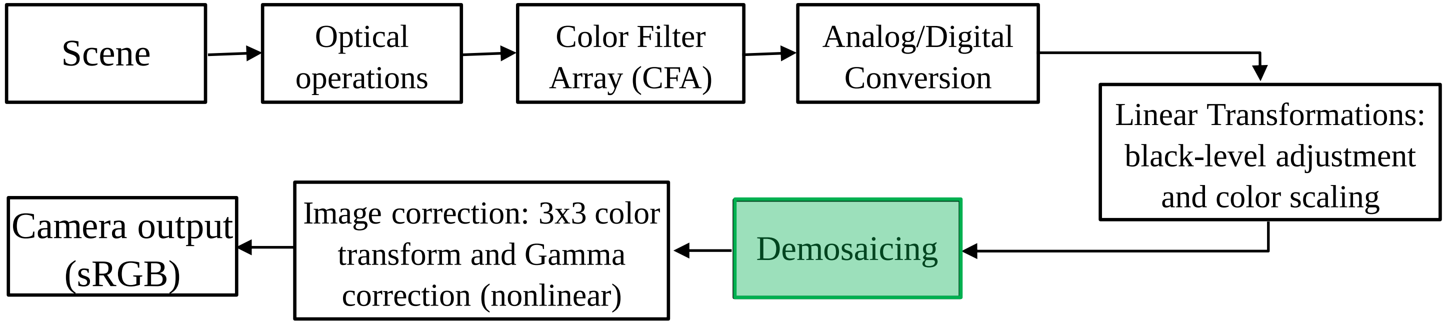

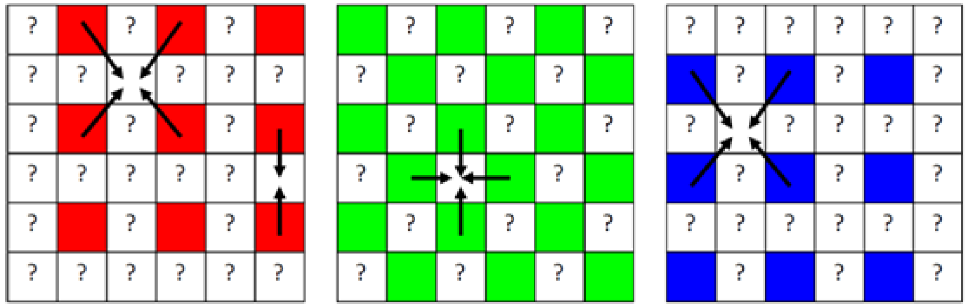

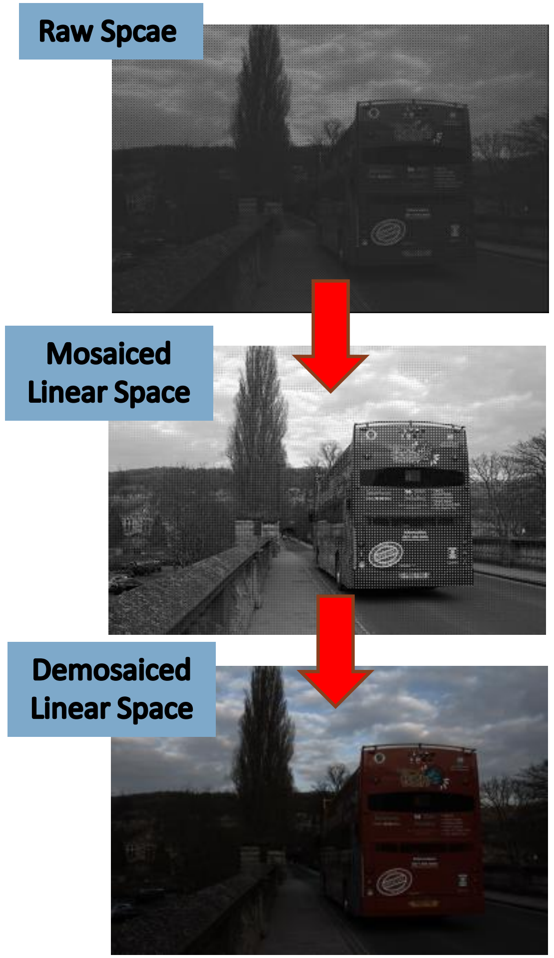

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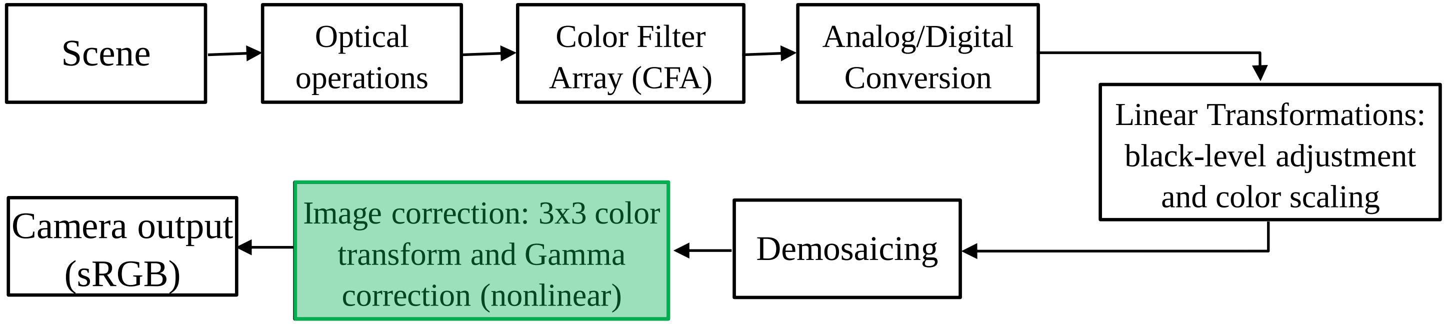
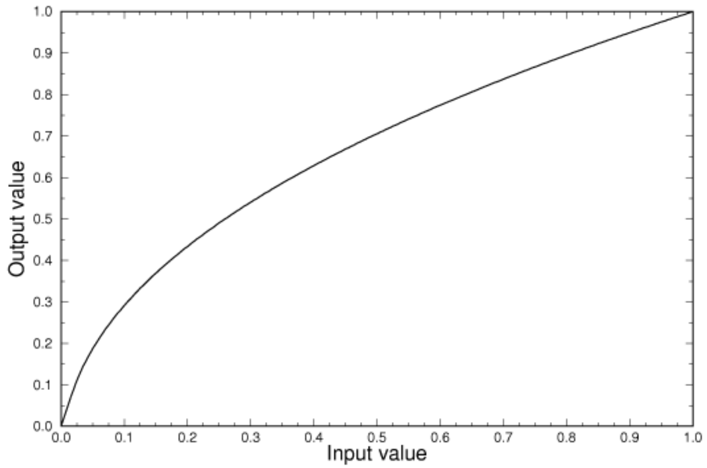
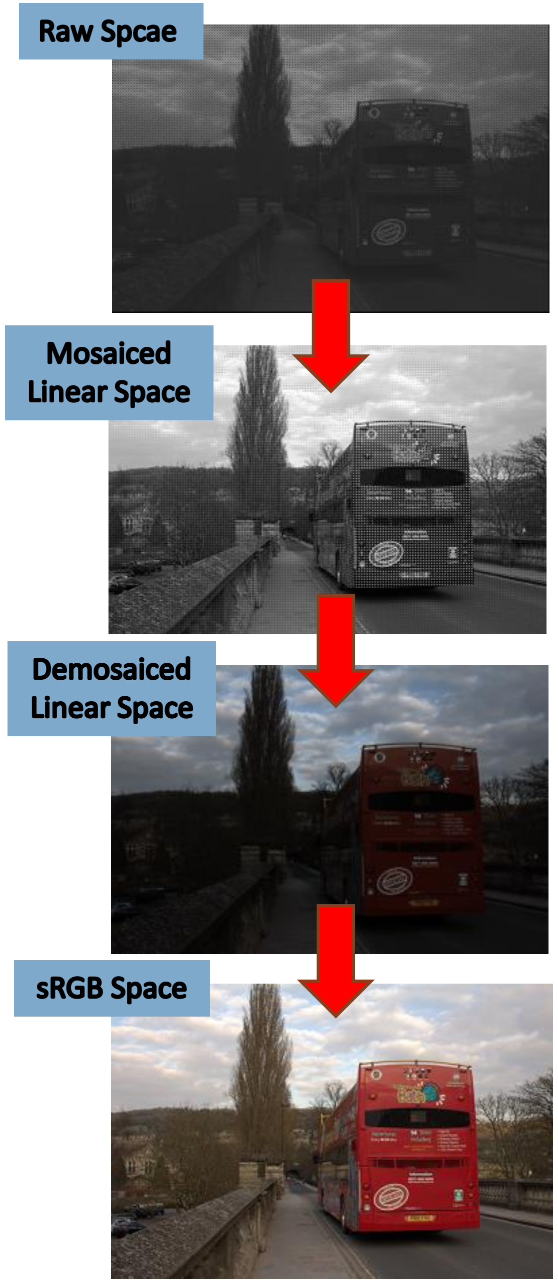




$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$



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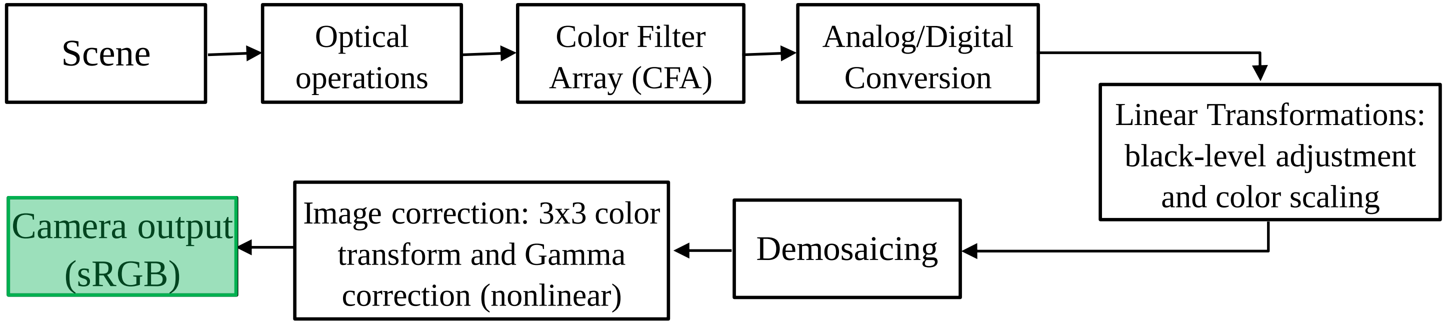

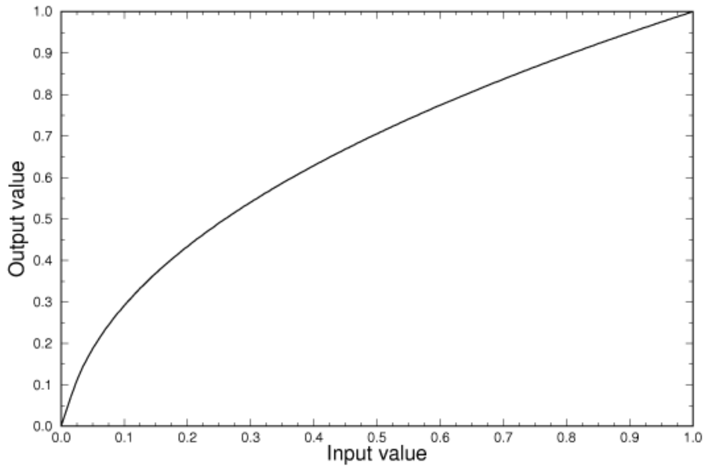

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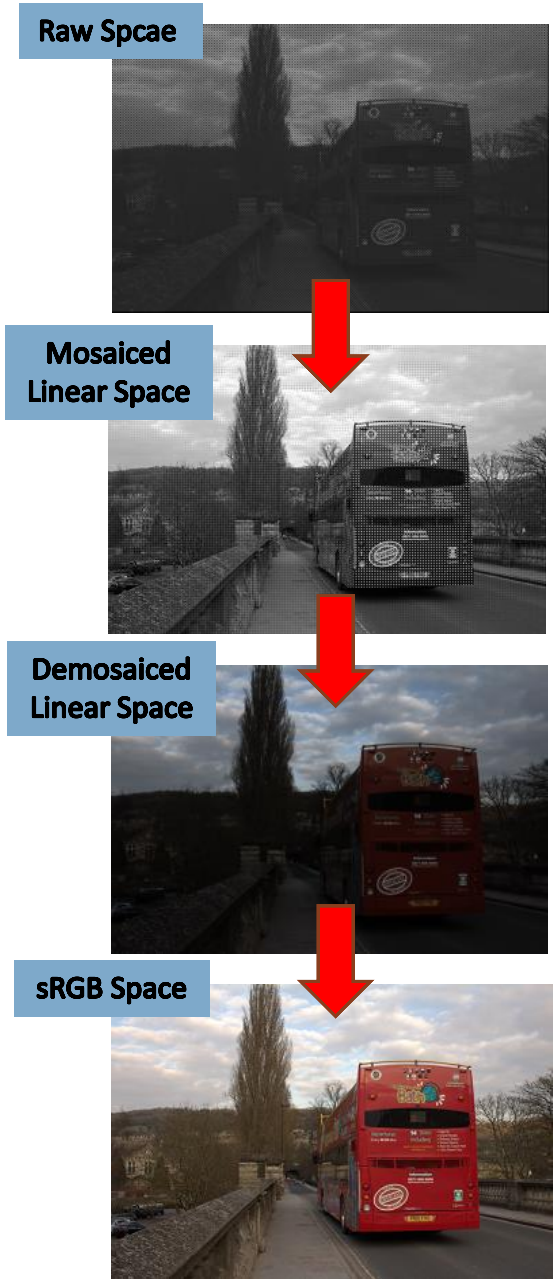

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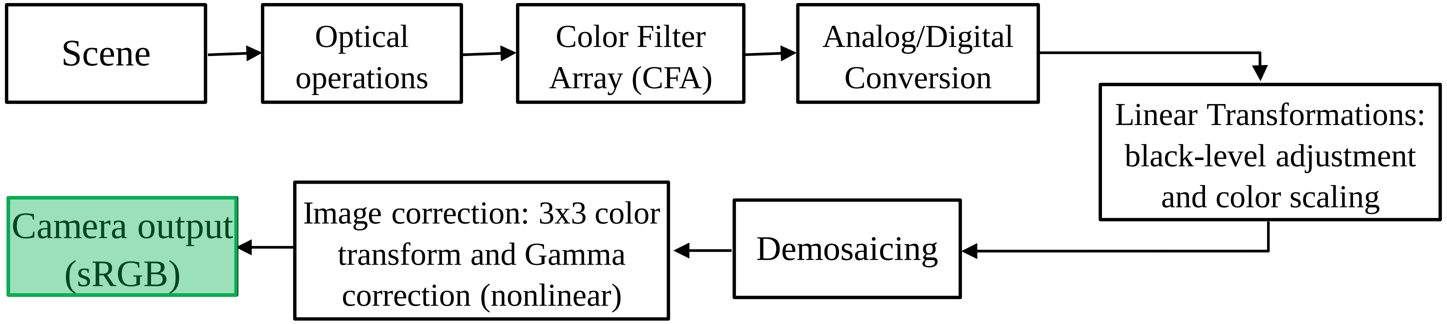
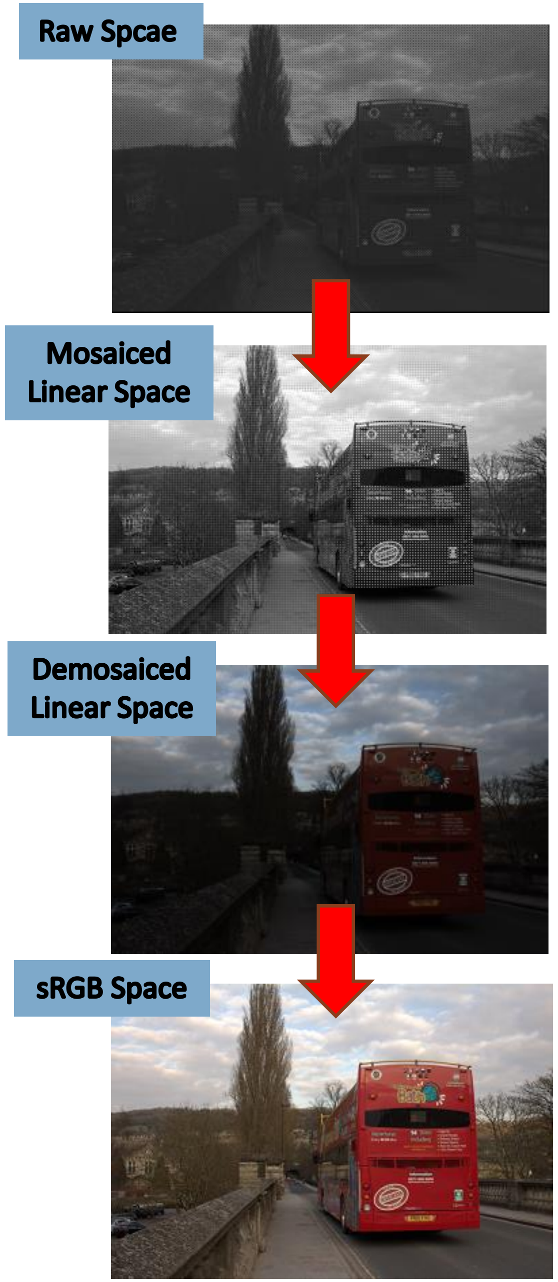
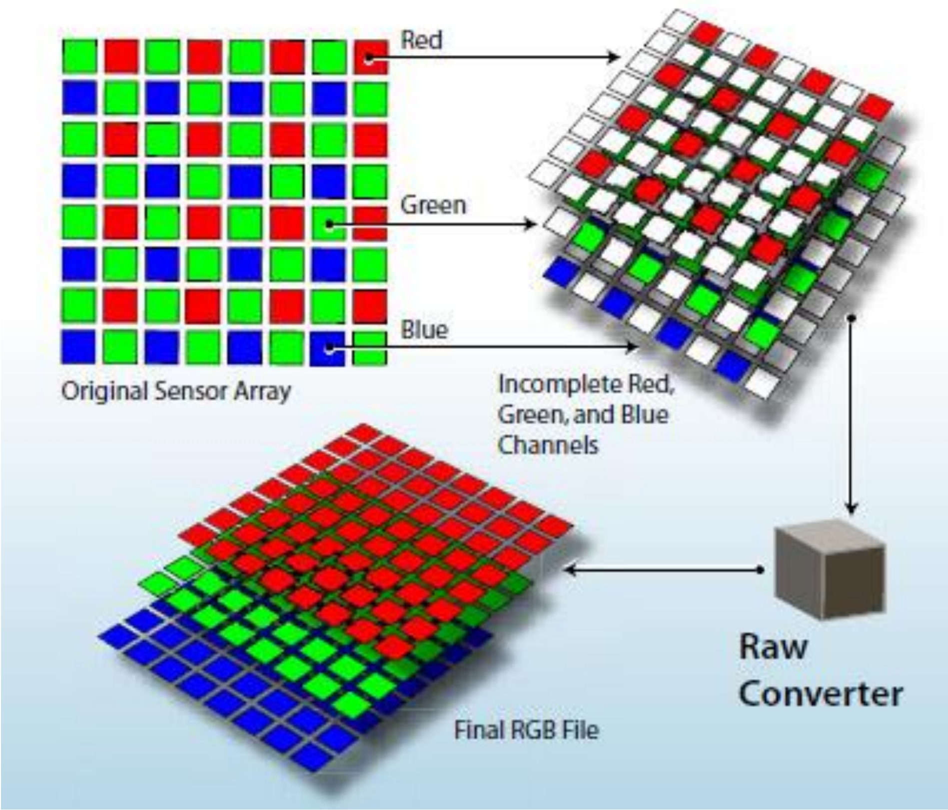




Images from: http://pho.to/media/images/digital/digital-techlology.jpg

Demosaicing

- Interpolating color-filter-array (CFA) samples to create full-resolution color images



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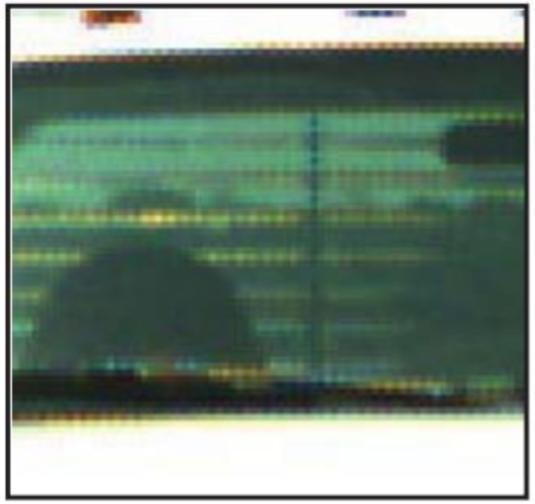

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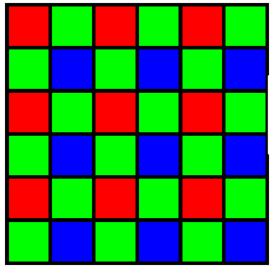

Bayer Pattern

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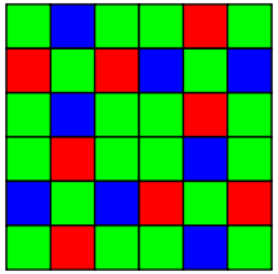
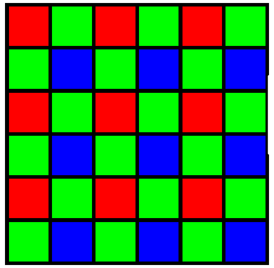


Fuji X-trans



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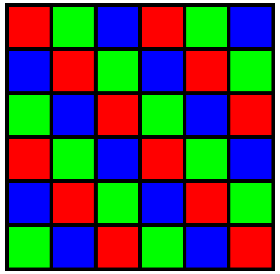

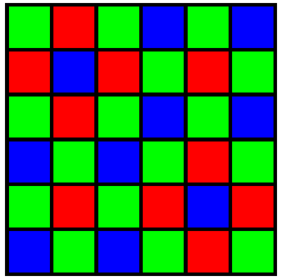

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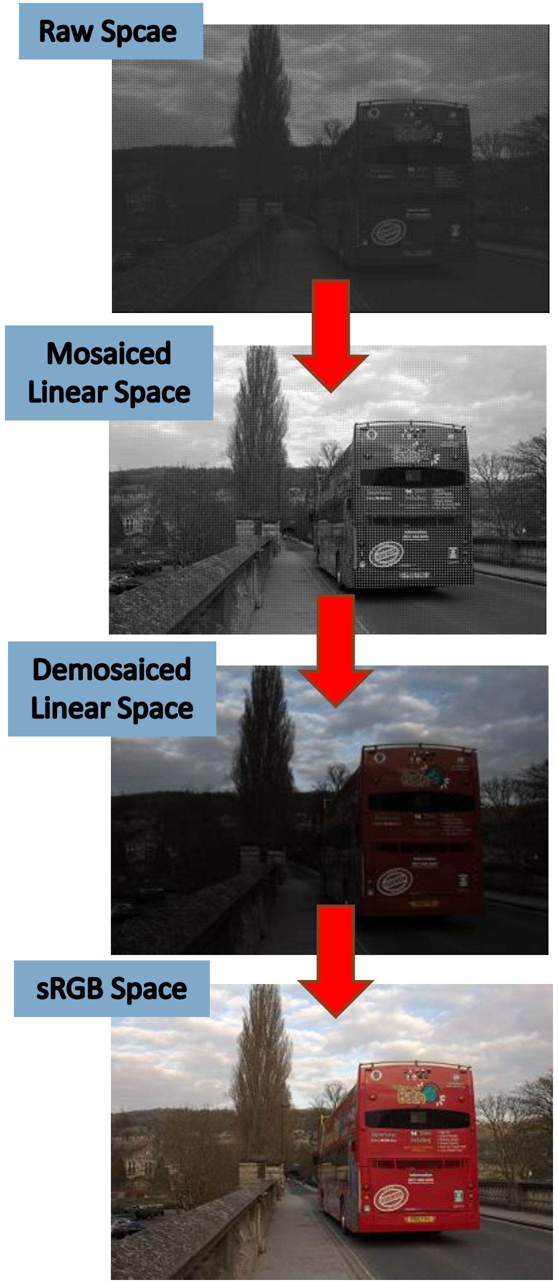

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- All method are engineered for sRGB images
    - Demosaicing is lacking a good dataset
- Many of low-level task could be done before/joint with demosaicing
    - Noise behaviour changes after demosaicing

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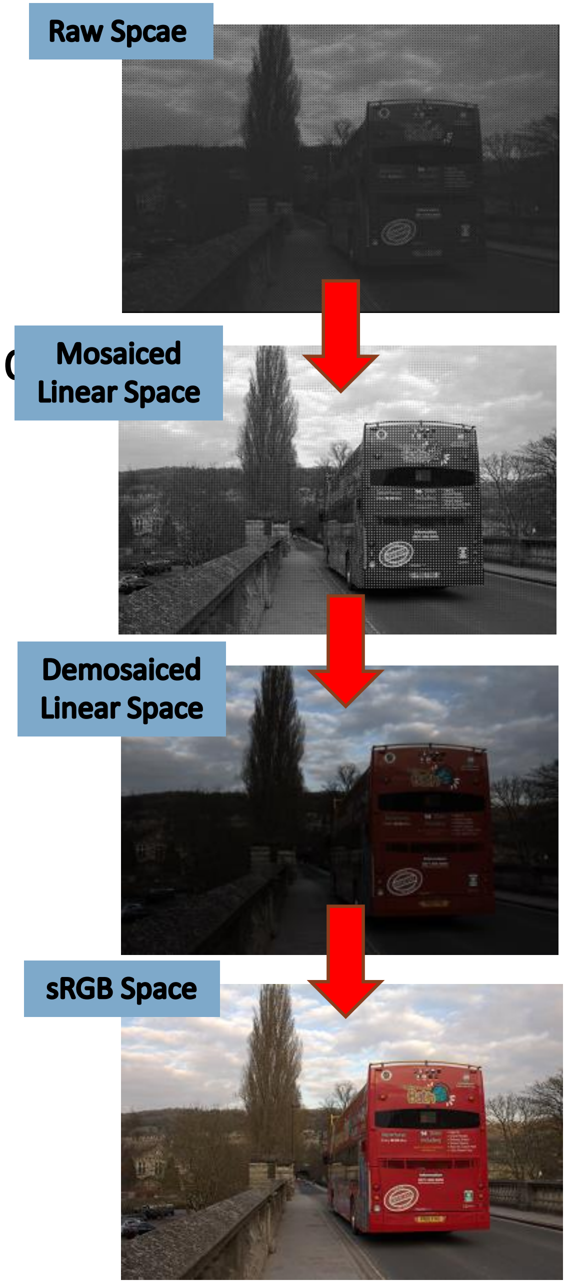

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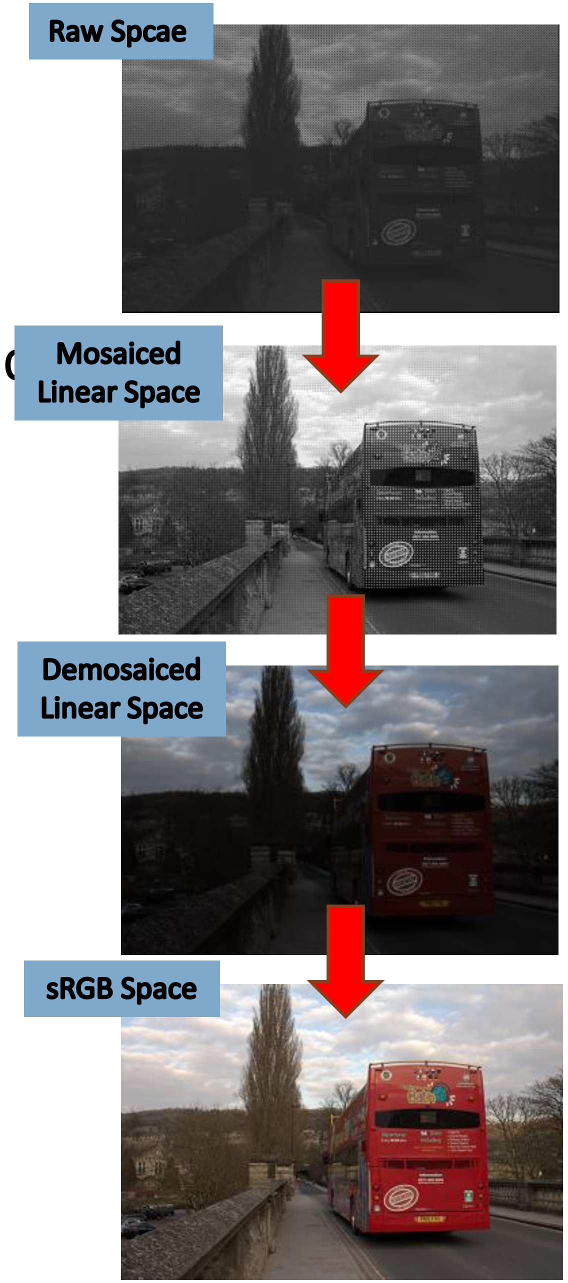

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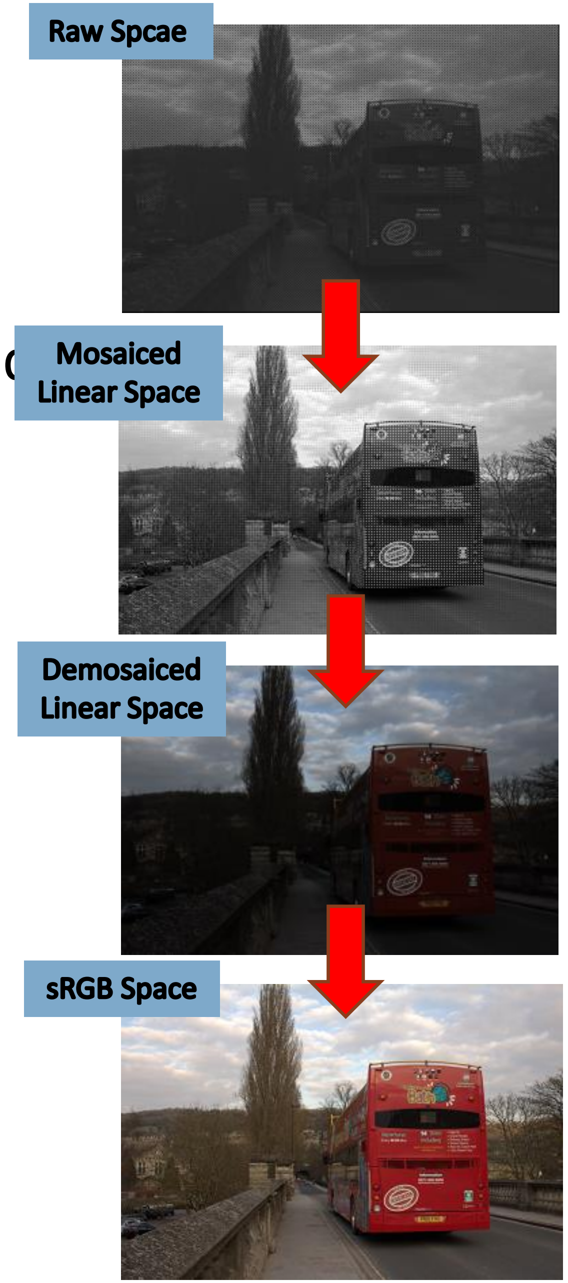

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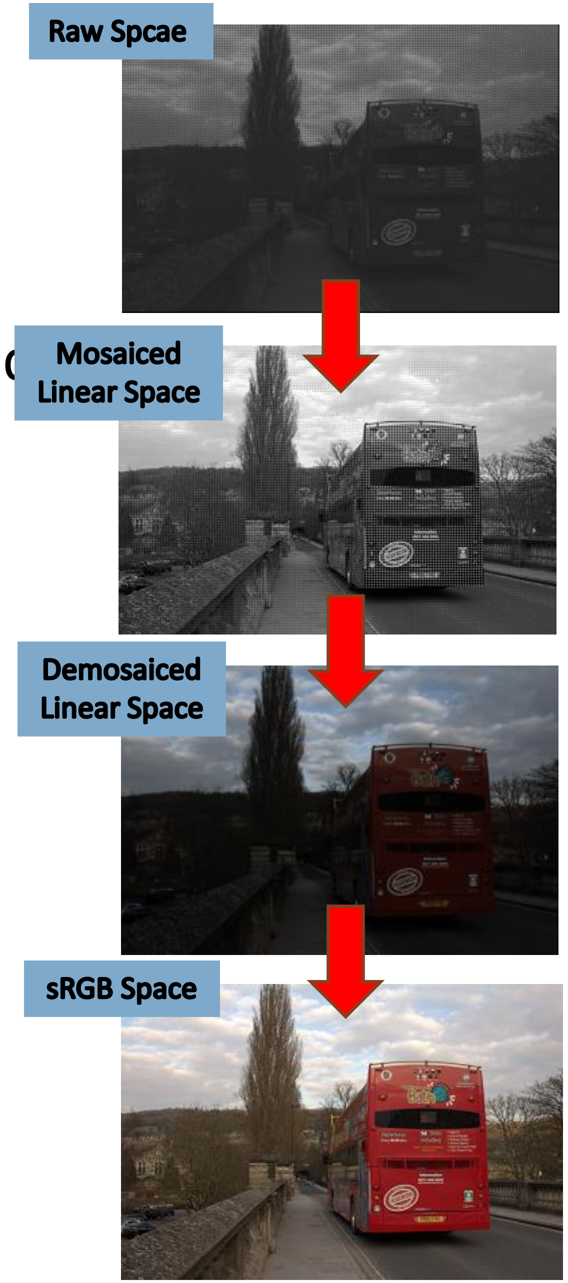
- Our model can perform **denoising jointly with demosaicing**.



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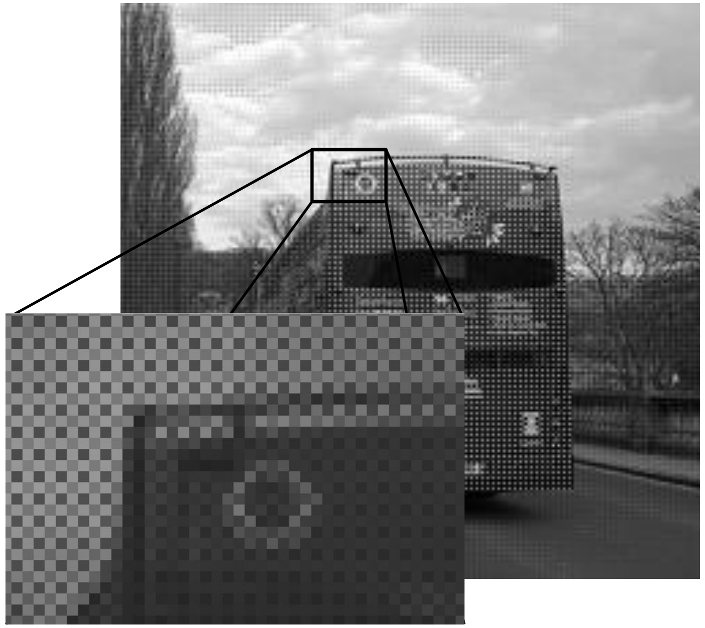

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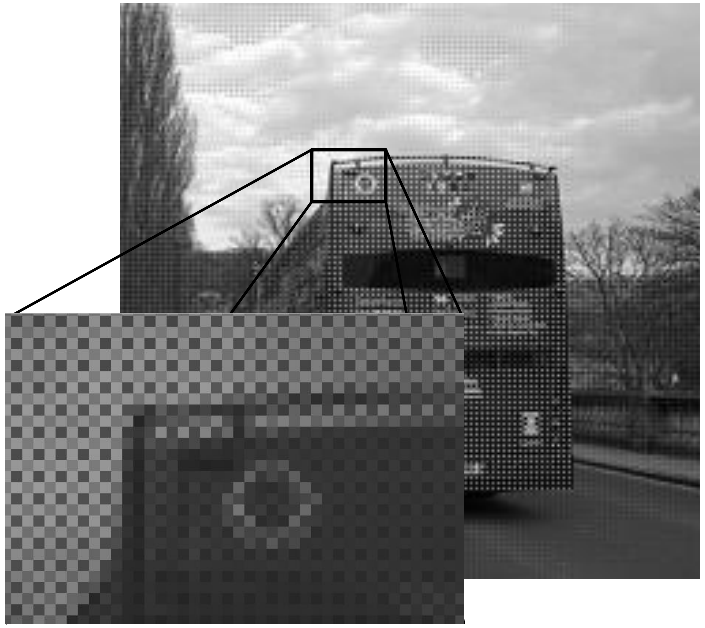

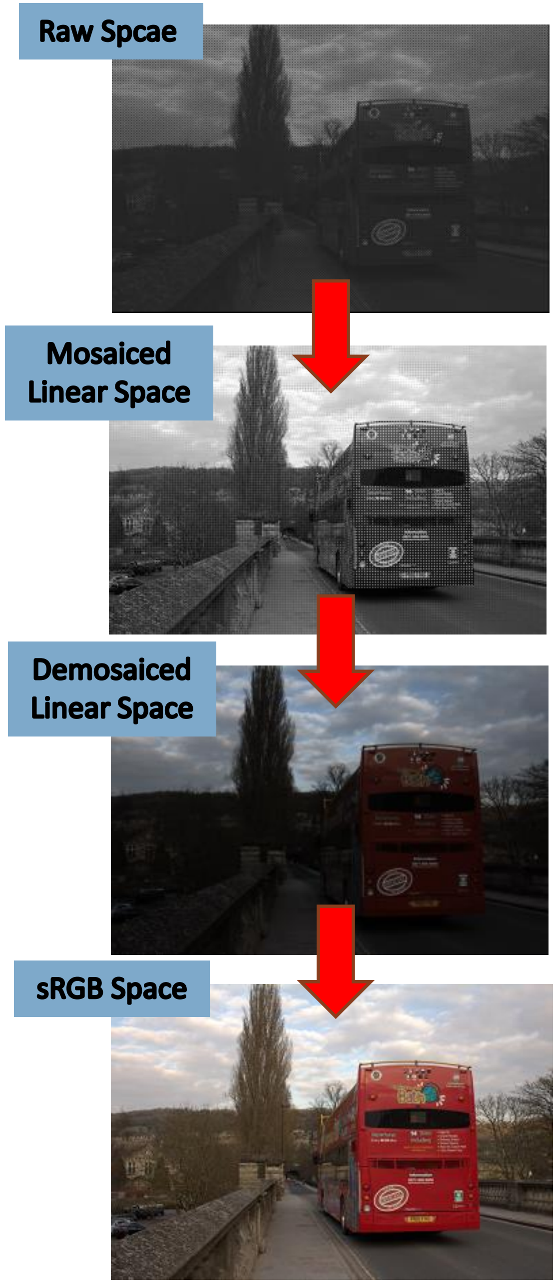

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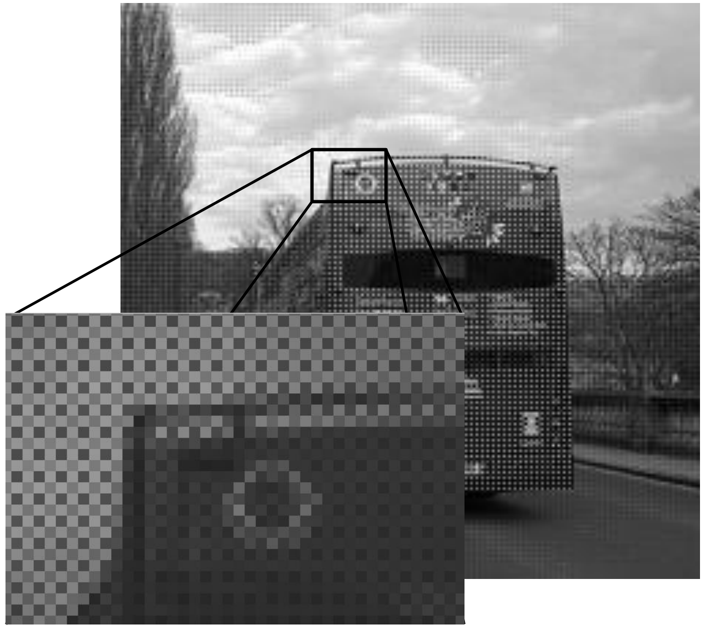

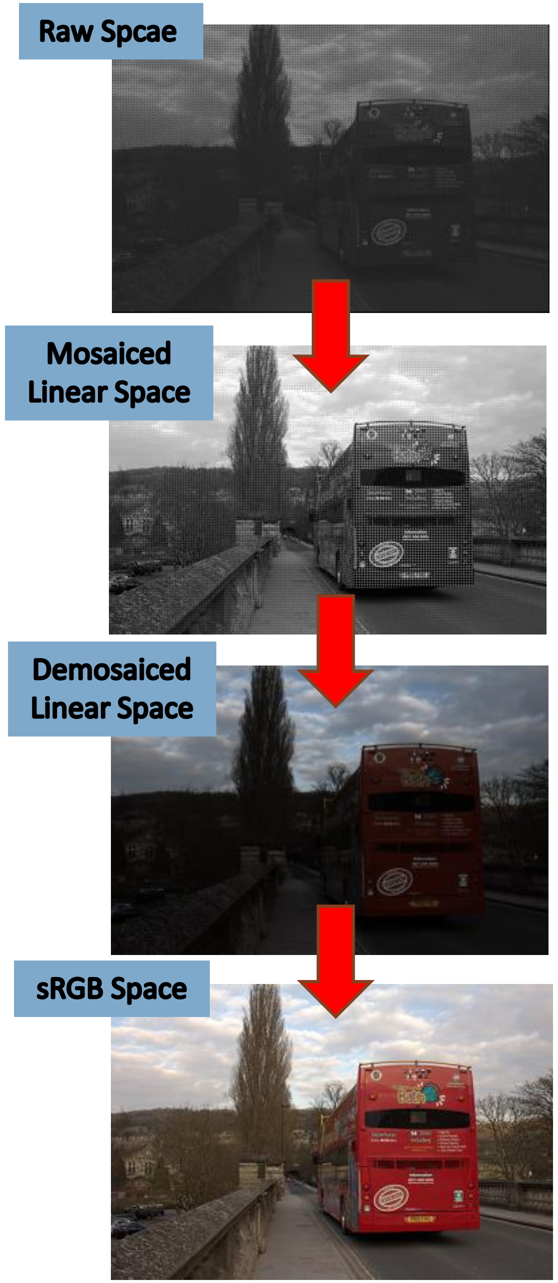

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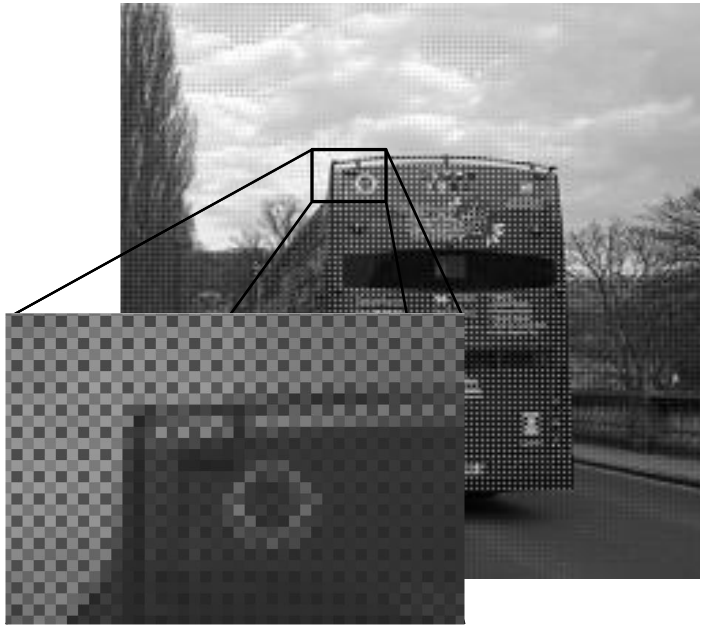

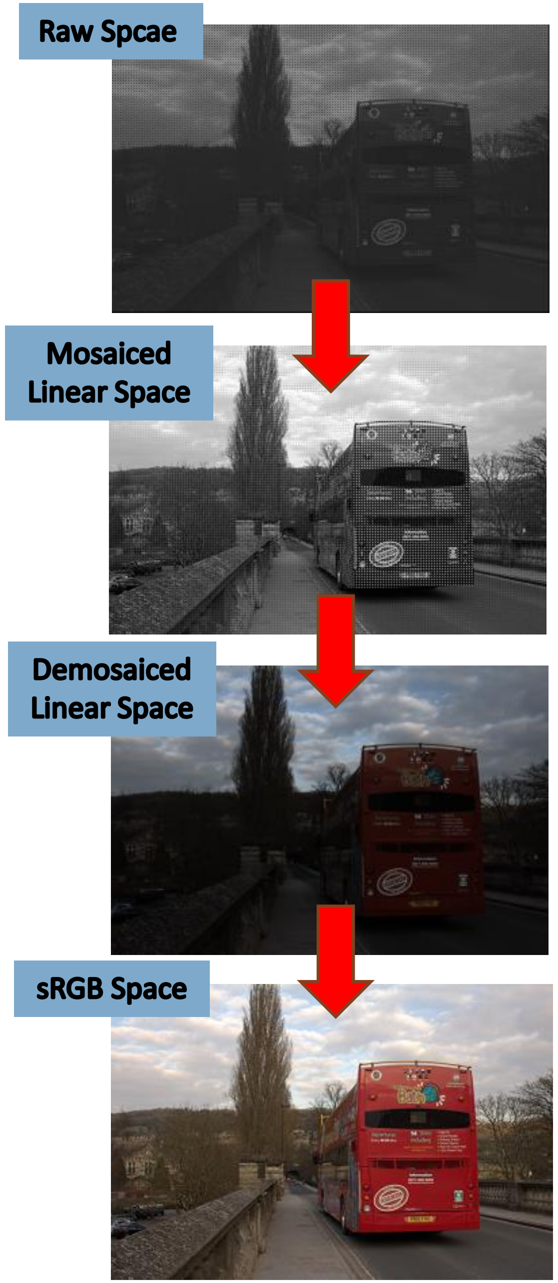

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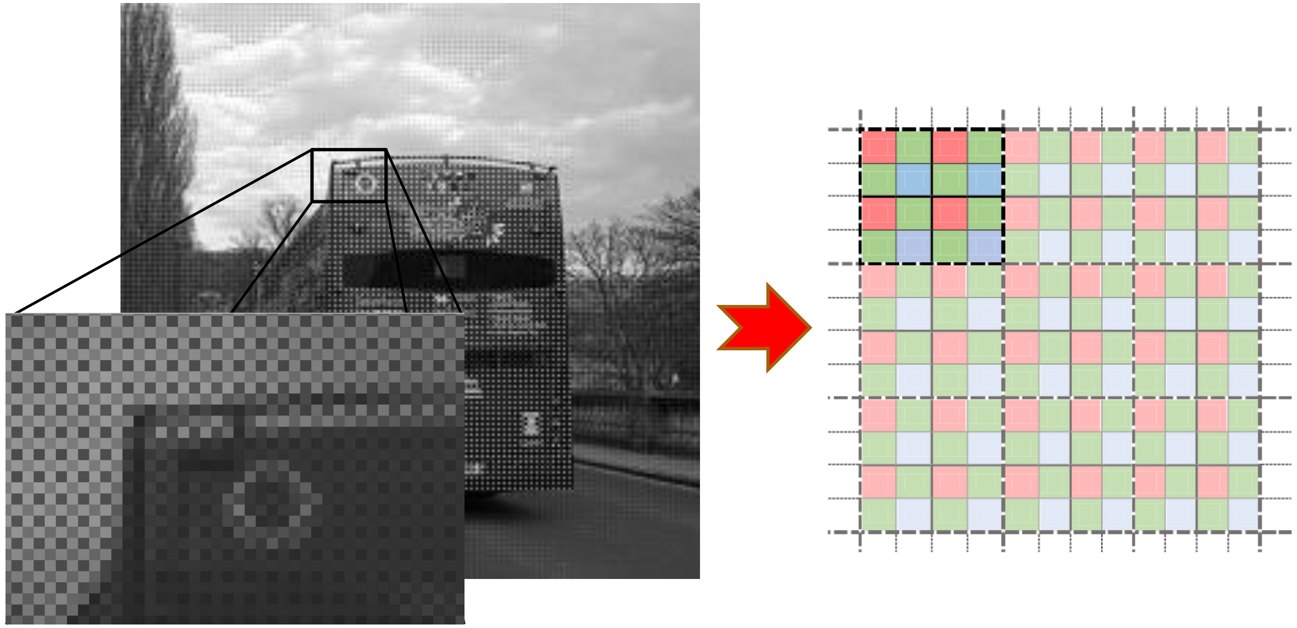

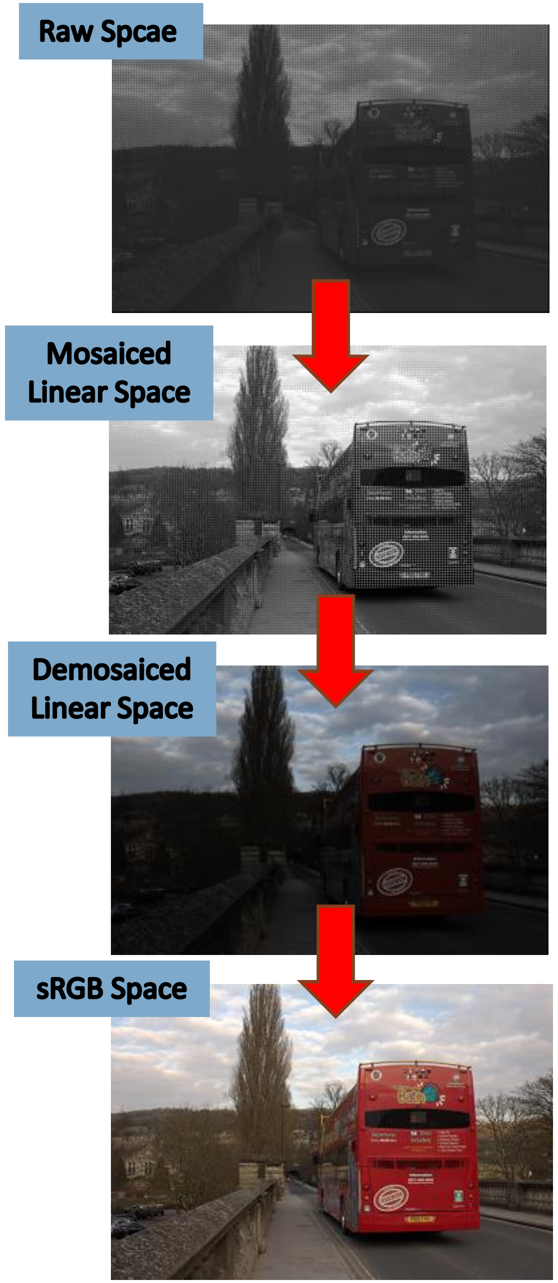

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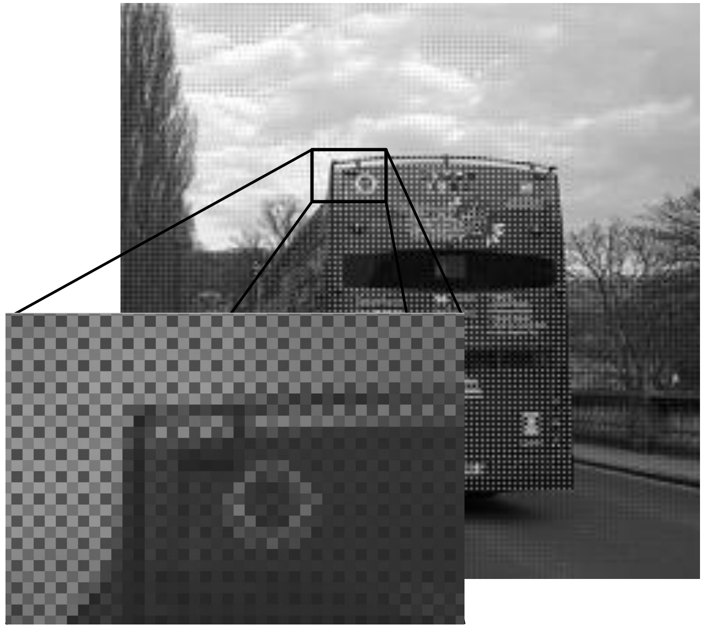

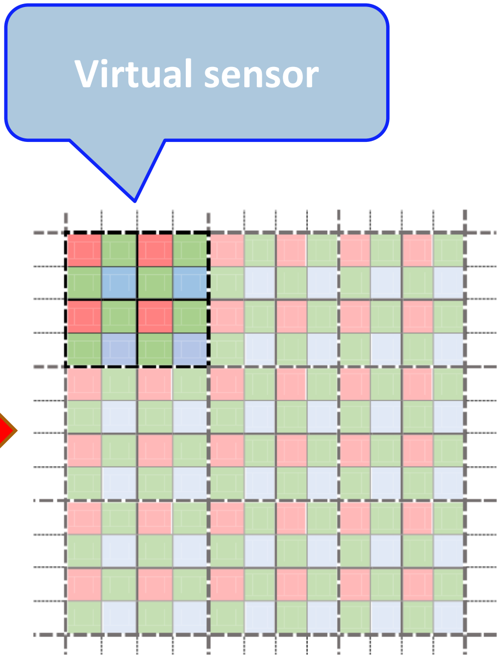

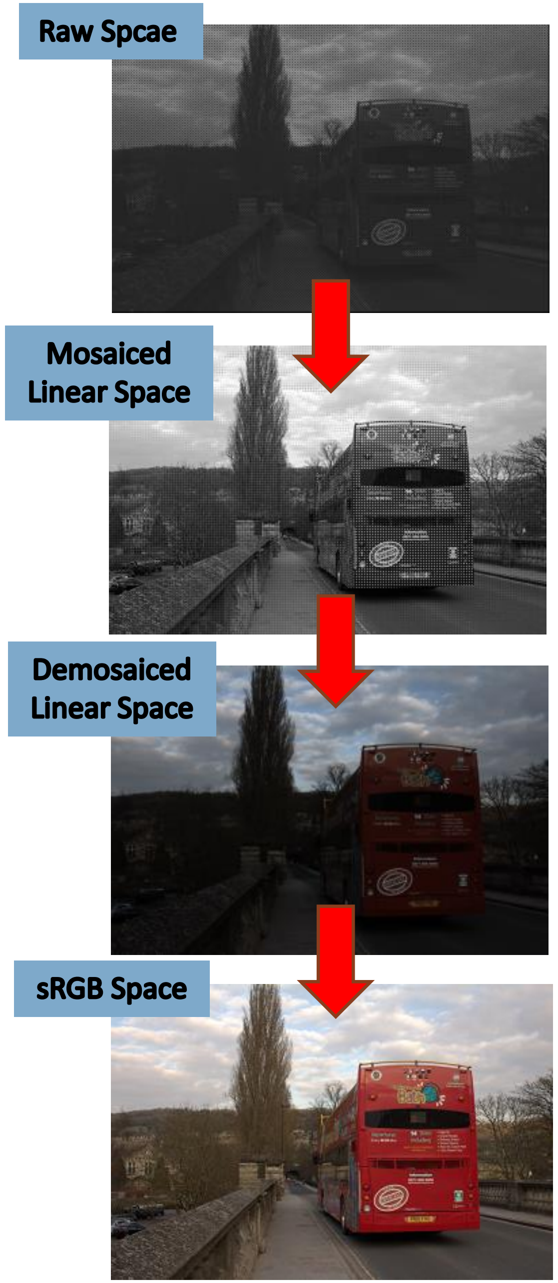

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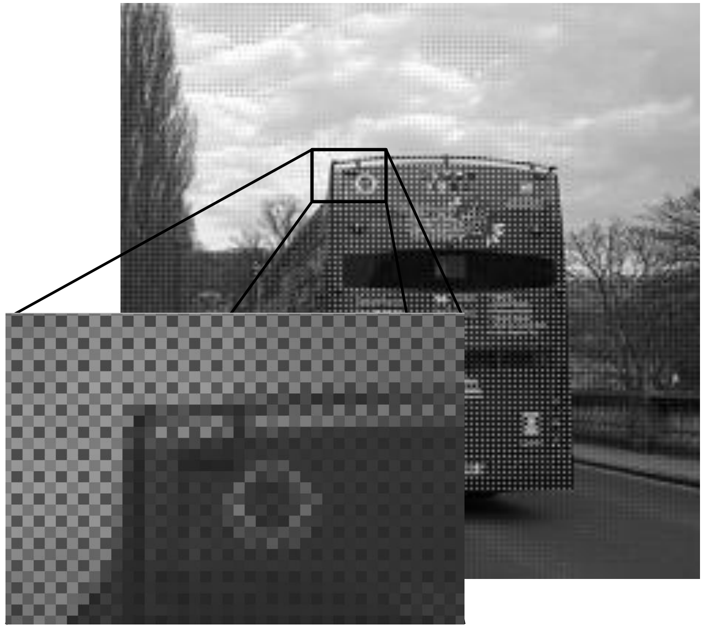

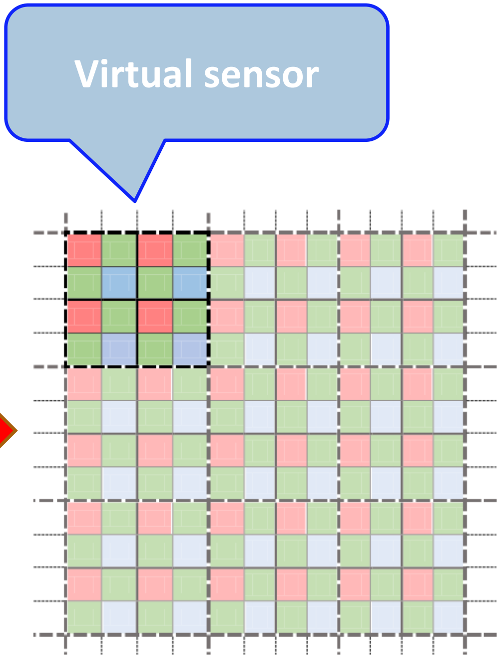

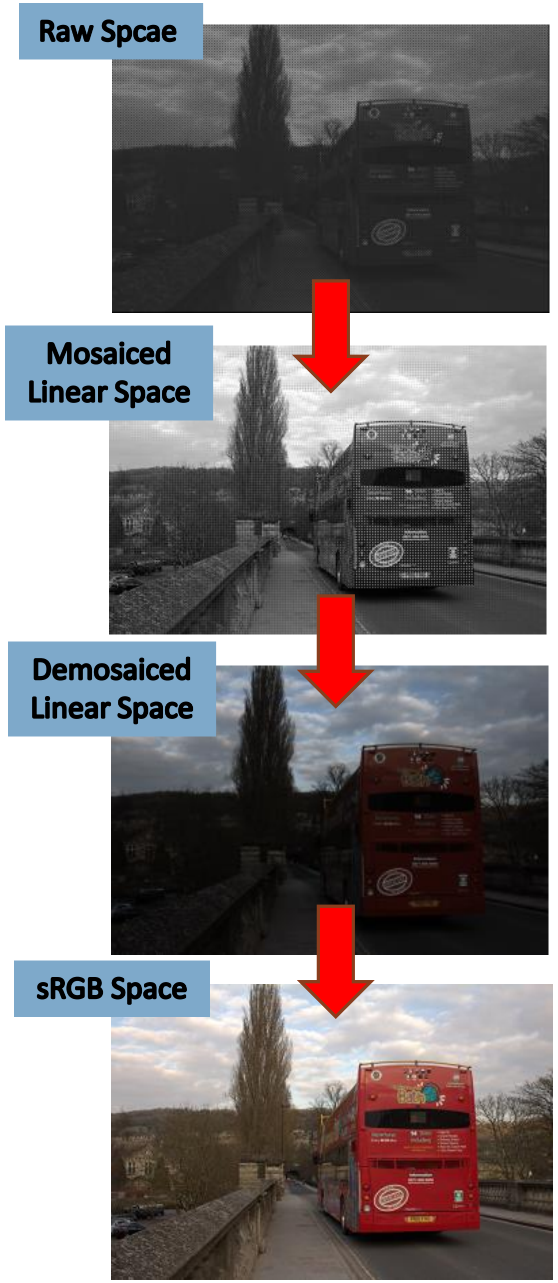

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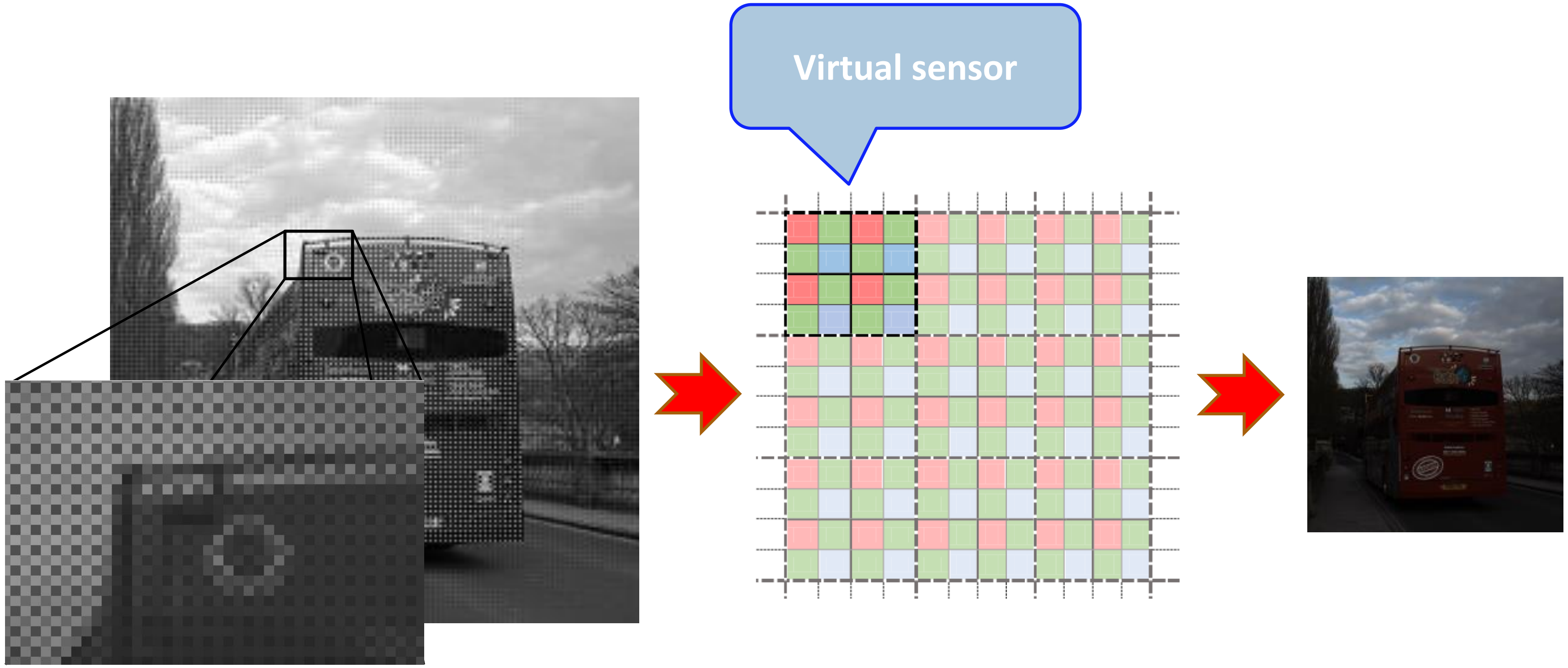

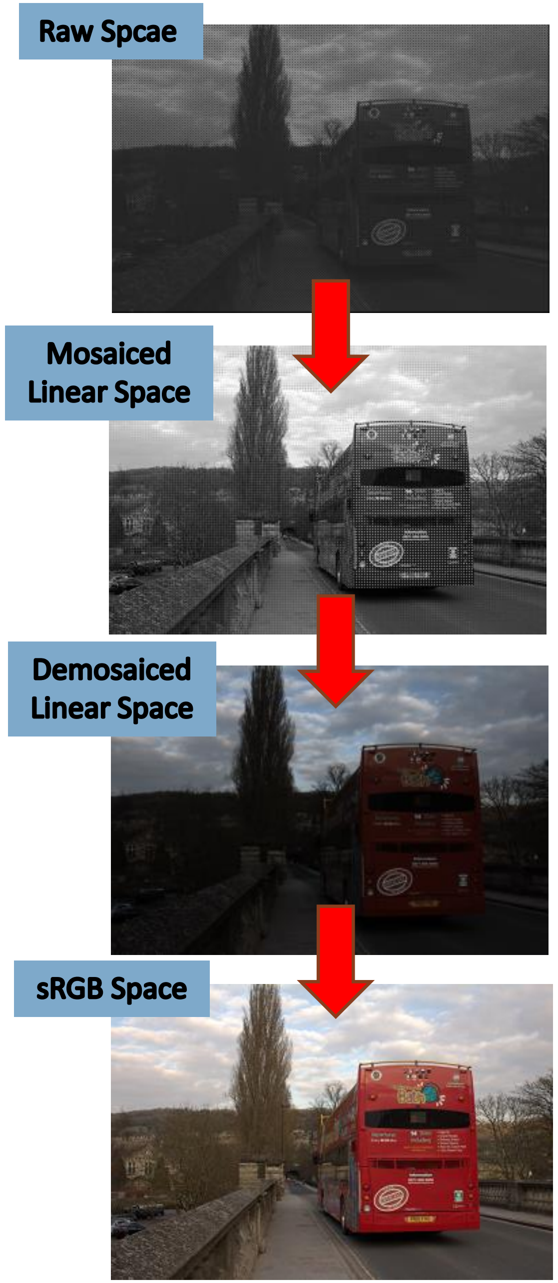

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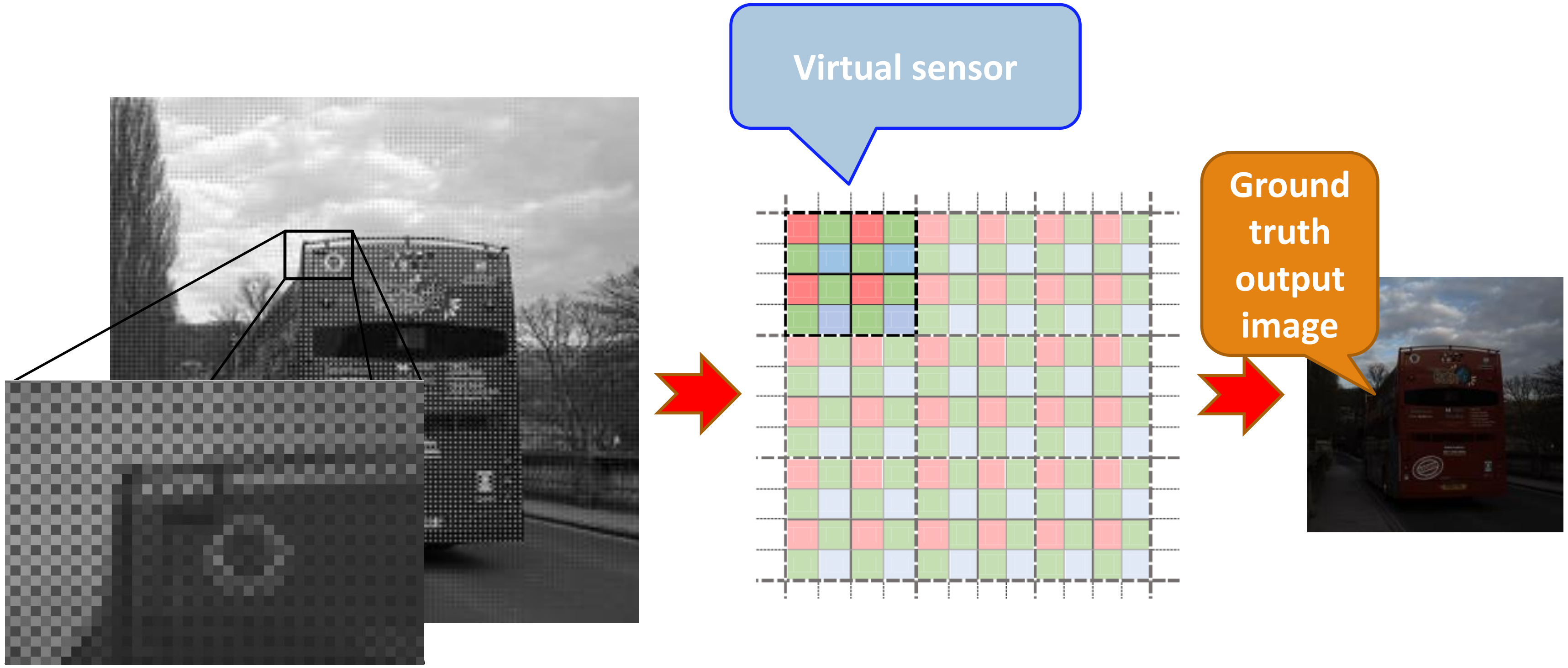

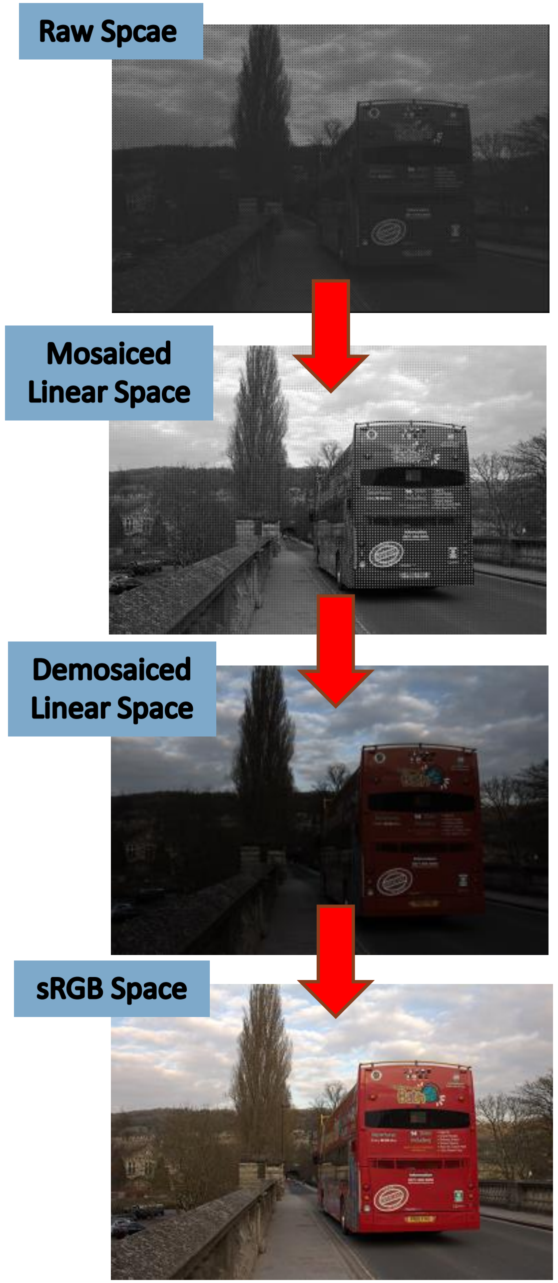

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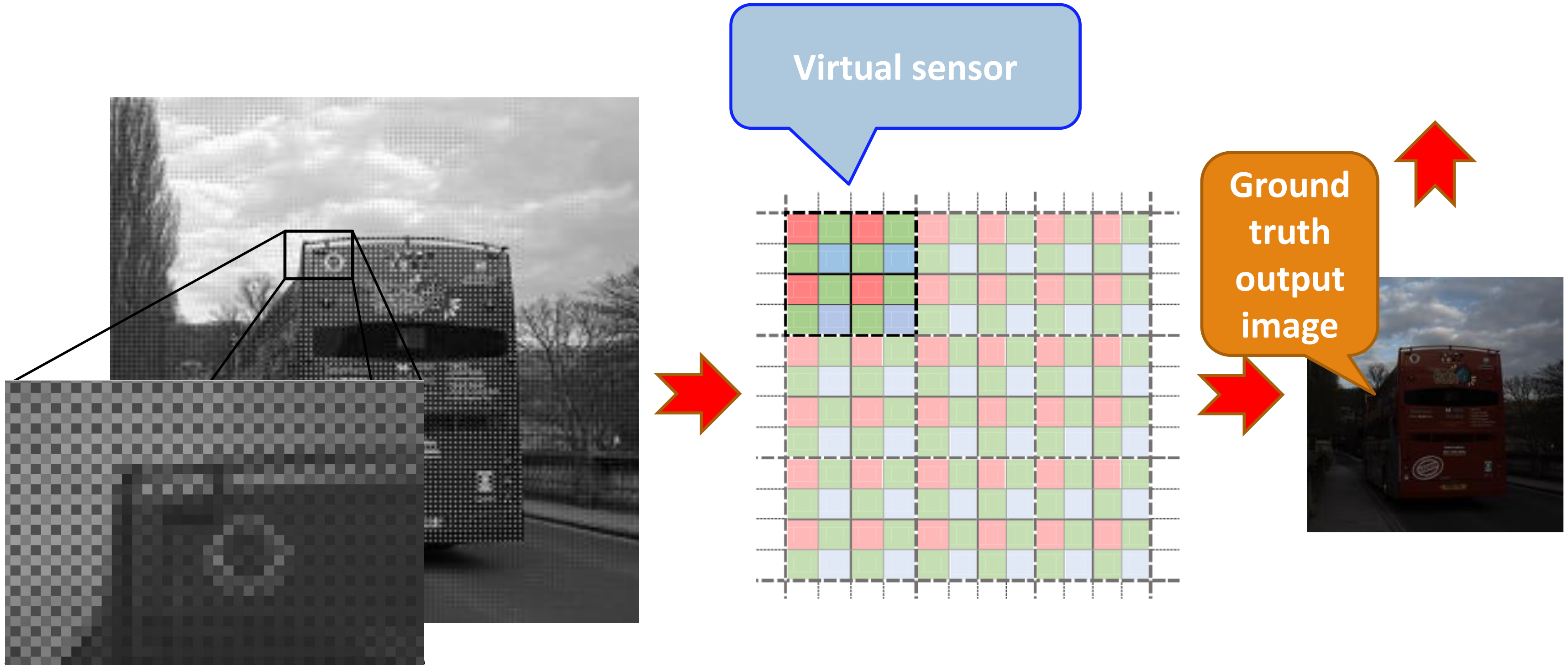

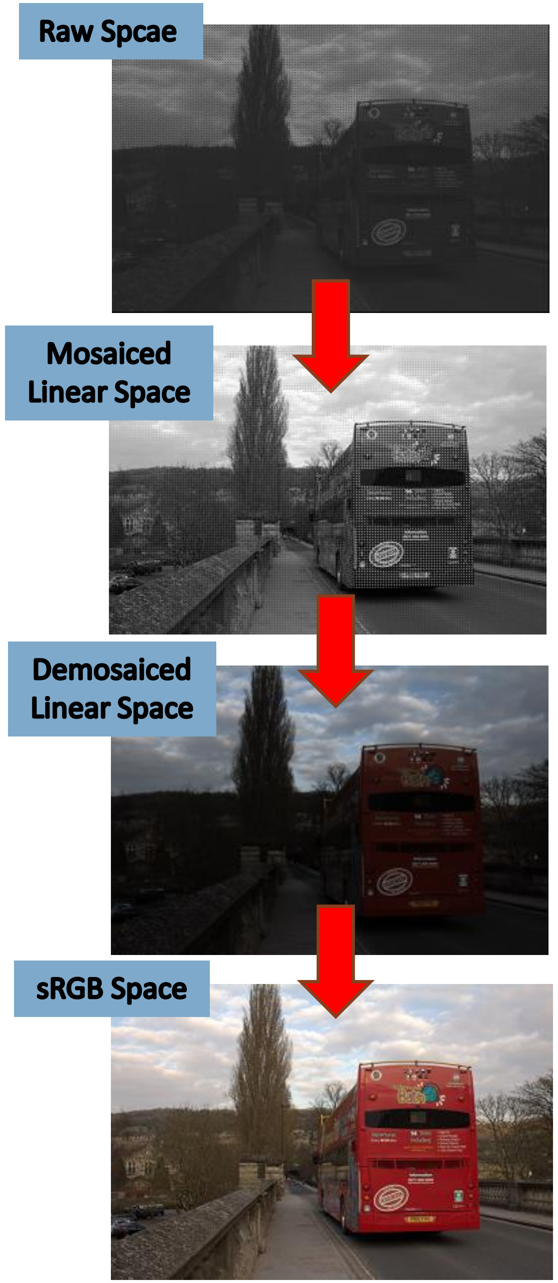

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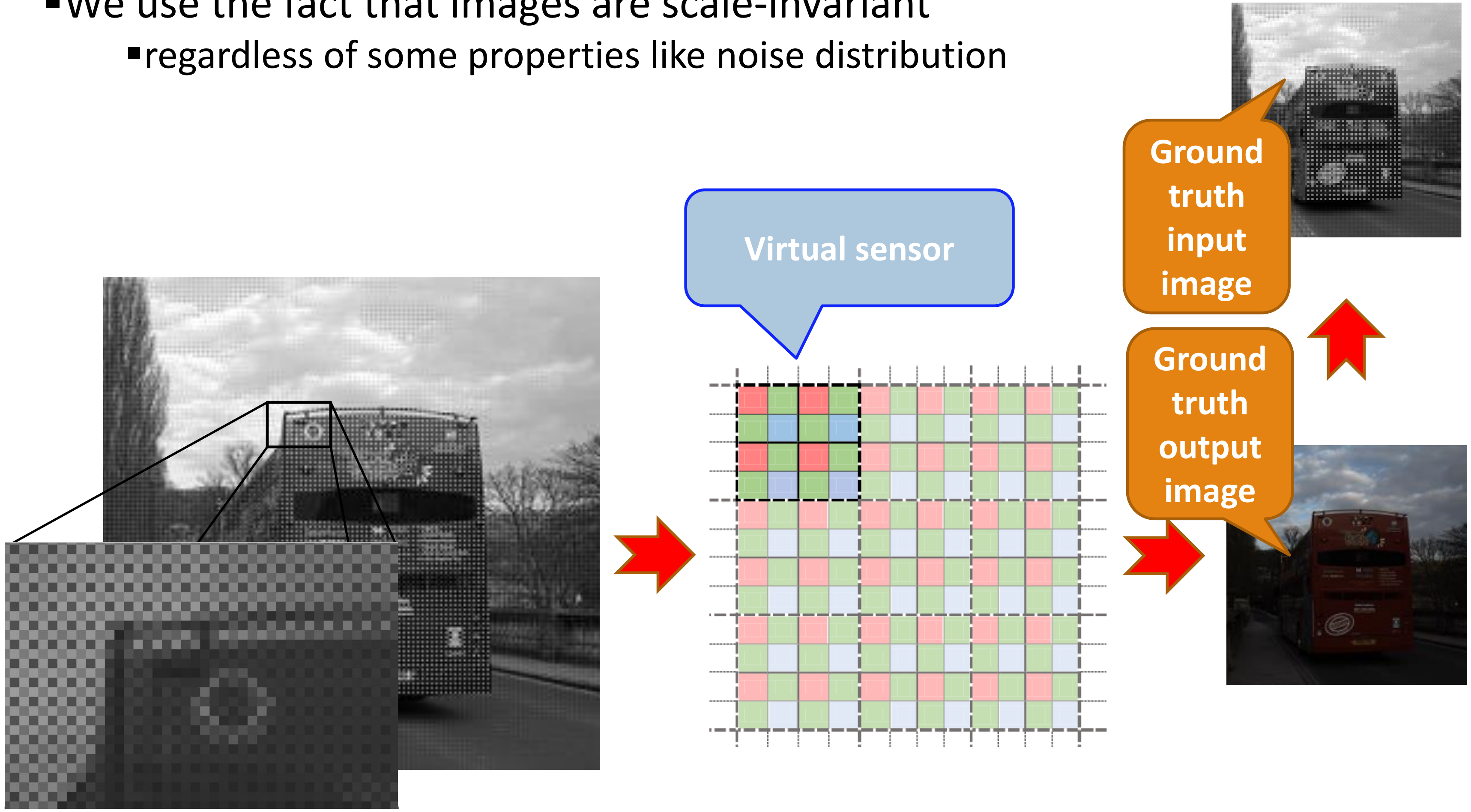

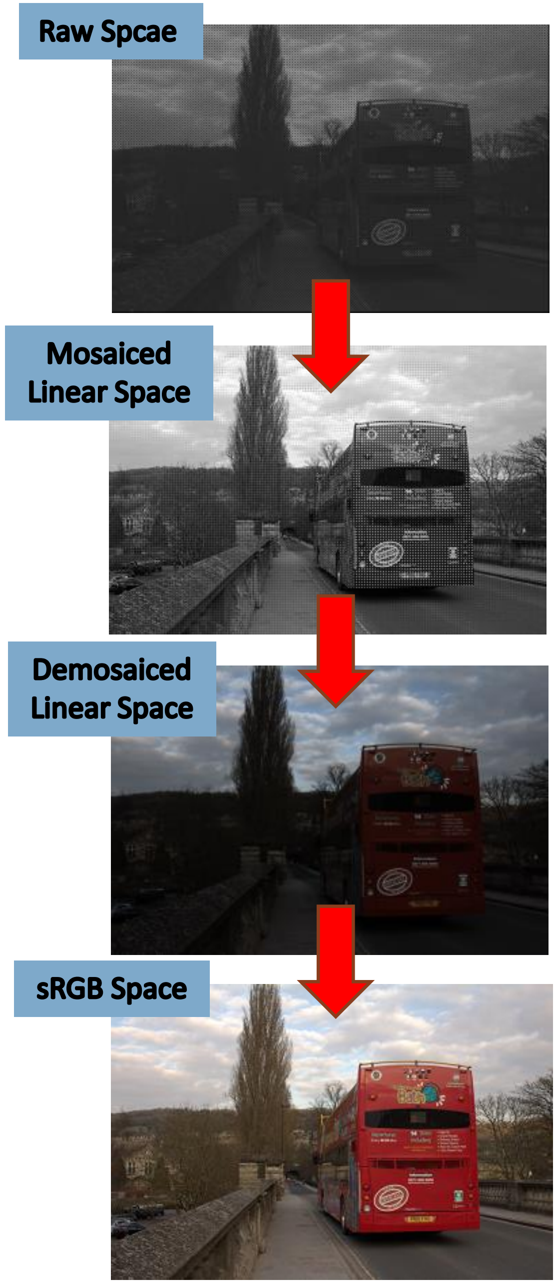

down-scaling strategies

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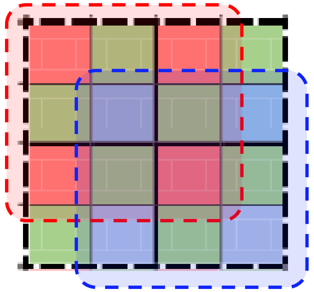

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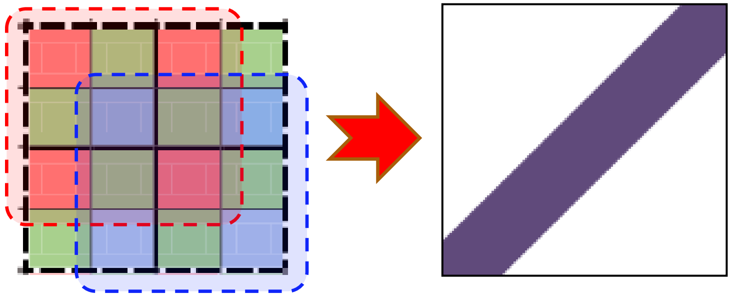

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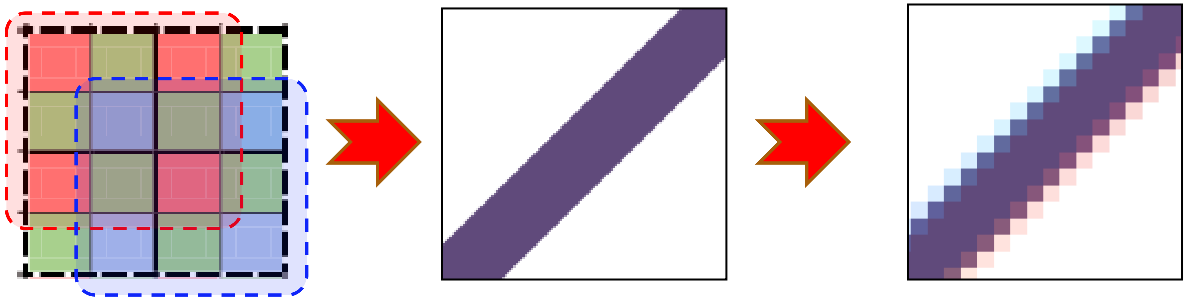

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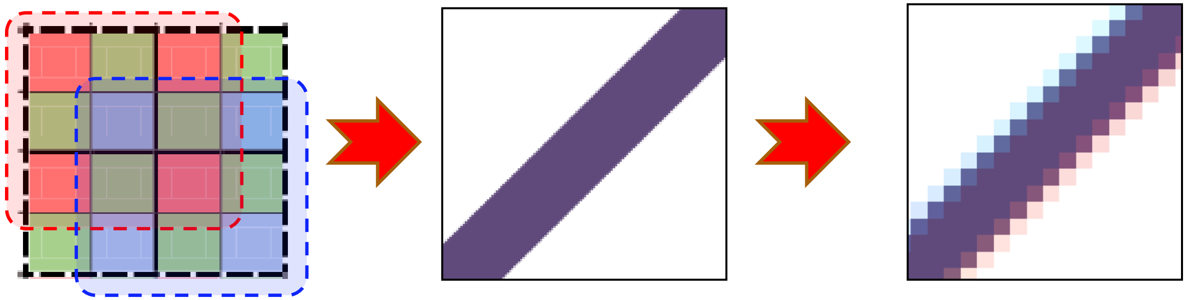

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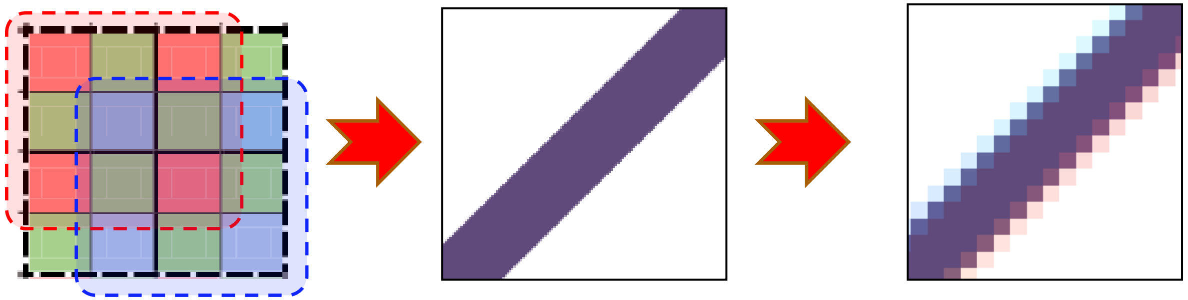

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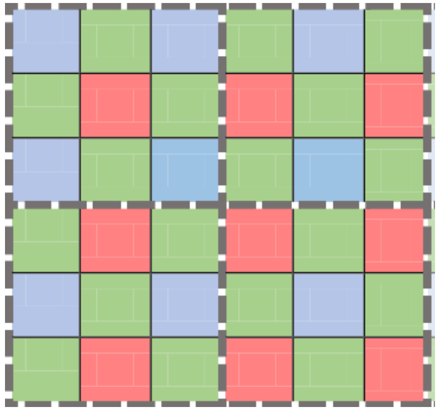

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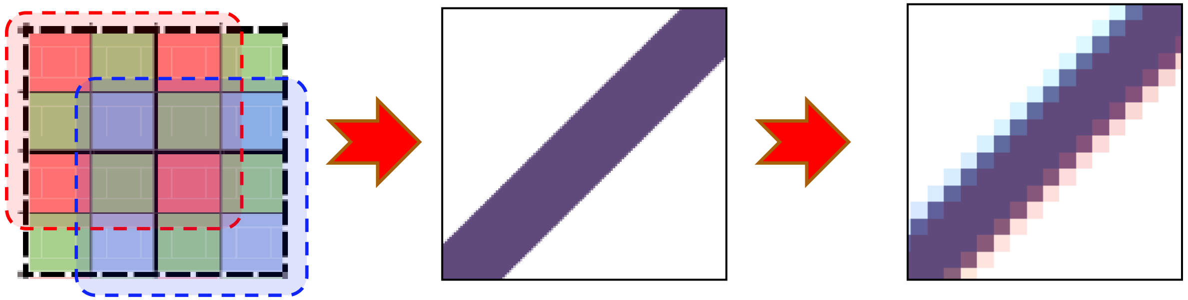

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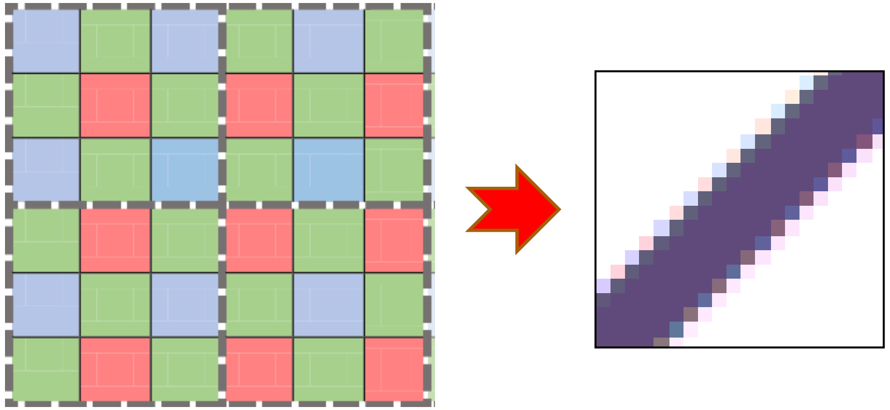

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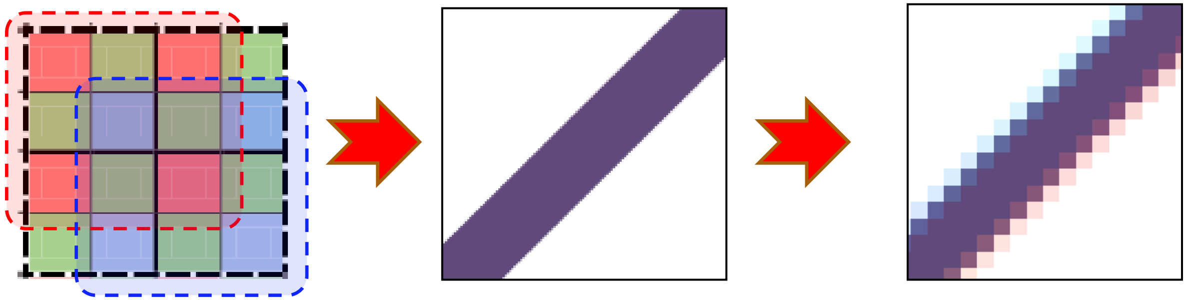

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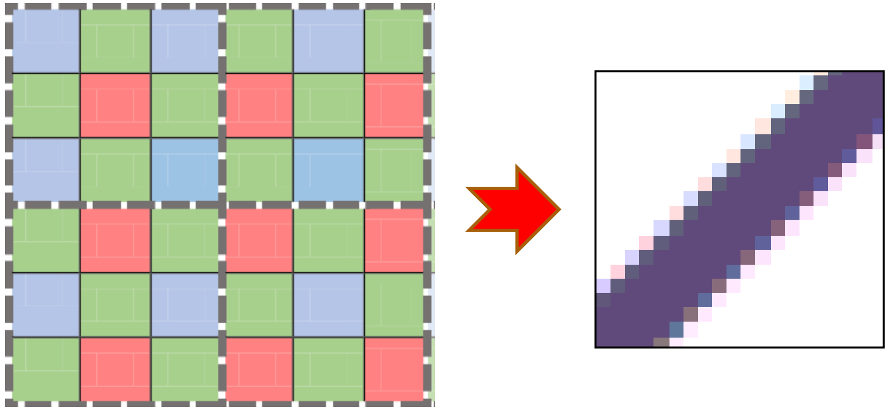
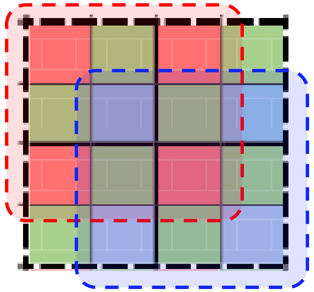


- We devised a strategy to compensate for the systematic bias when the size of the window is even

Max-Ent down-scaling

- Goal:
  - Want to bring the **center of the mass**, for each color, to the center of each block



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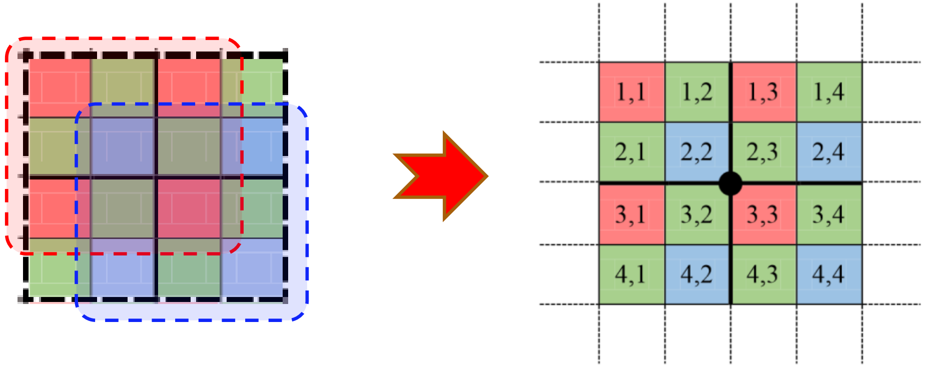

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$$
\begin{cases}
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\sum_{x,y} p(x,y) = 1 \\
p(x,y) \geq 0, \forall x, y \\
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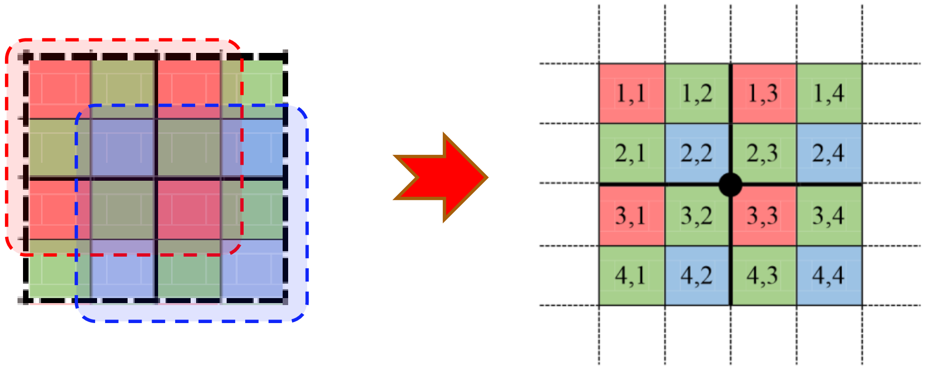
$$



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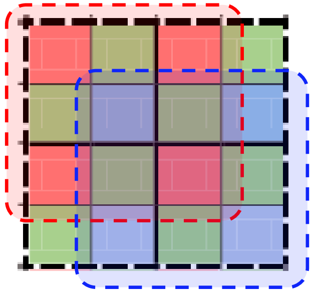

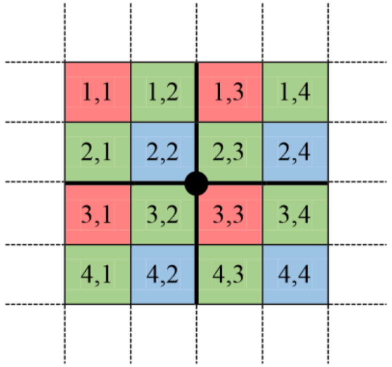

$$p_r(x,y) = \frac{1}{16}\left[\begin{array}{cc|cc} 1 & 0 & 3 & 0 \\ 0 & 0 & 0 & 0 \\ \hline 3 & 0 & 9 & 0 \\ 0 & 0 & 0 & 0 \end{array}\right], \quad p_b(x,y) = \frac{1}{16}\left[\begin{array}{cc|cc} 0 & 0 & 0 & 0 \\ 0 & 9 & 0 & 3 \\ \hline 0 & 0 & 0 & 0 \\ 0 & 3 & 0 & 1 \end{array}\right] \quad p_g(x,y) = \frac{1}{8}\left[\begin{array}{cc|cc} 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \\ \hline 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \end{array}\right]$$

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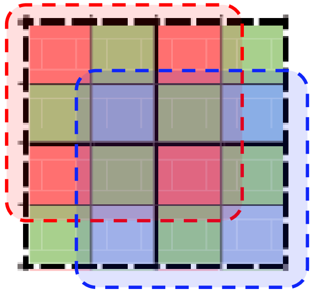

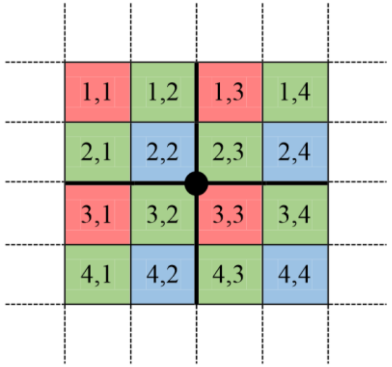

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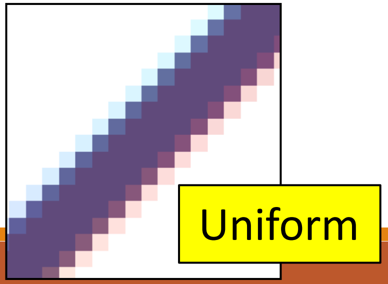

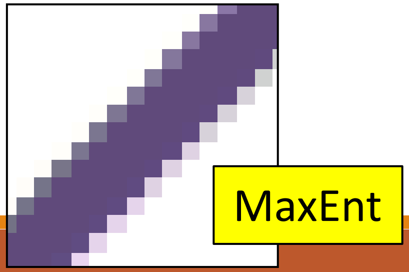

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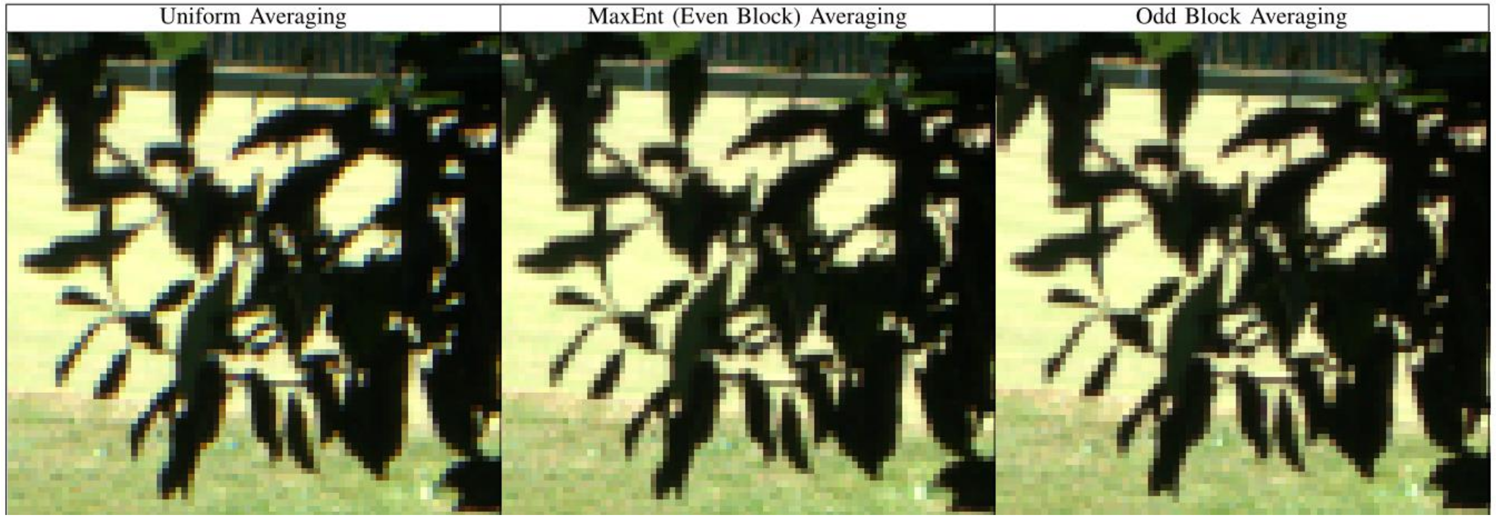

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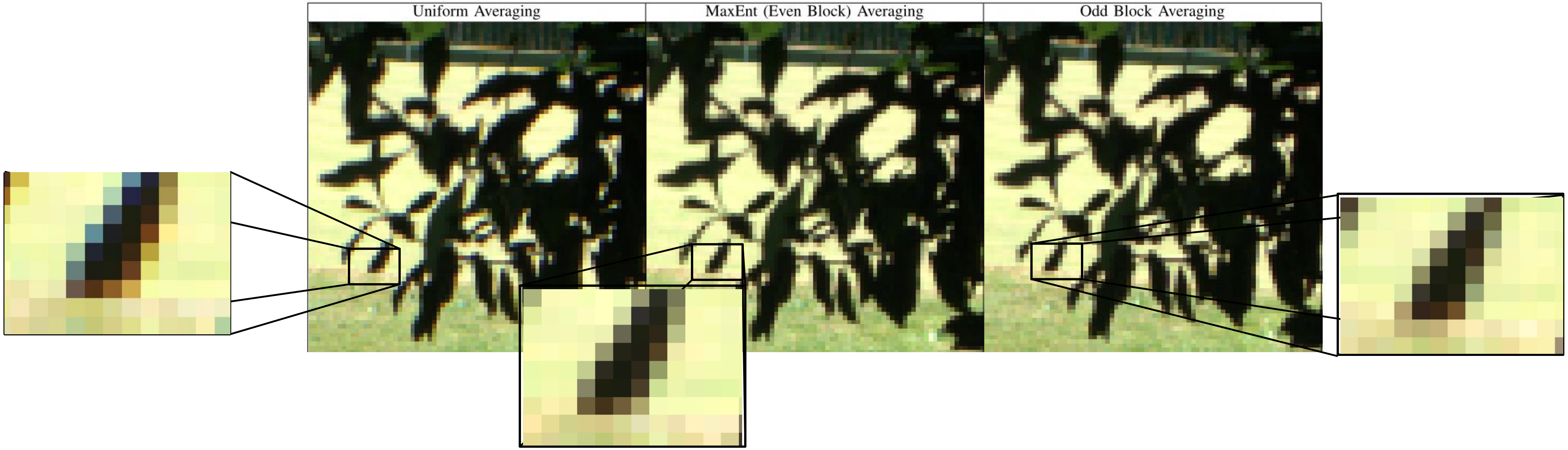

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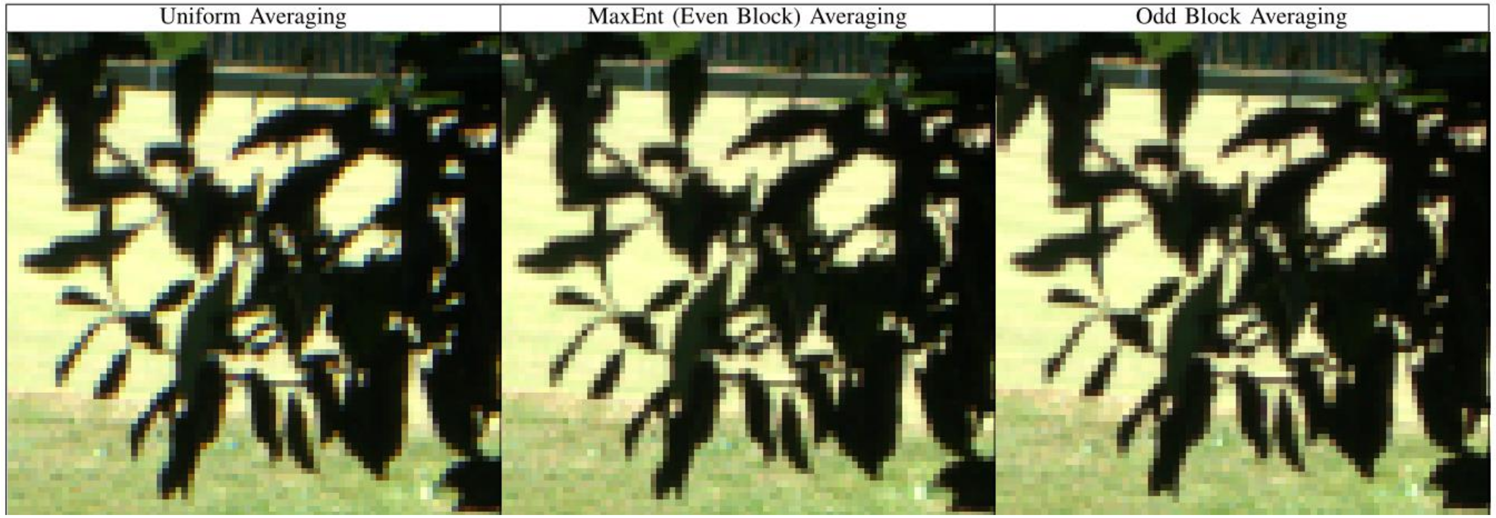

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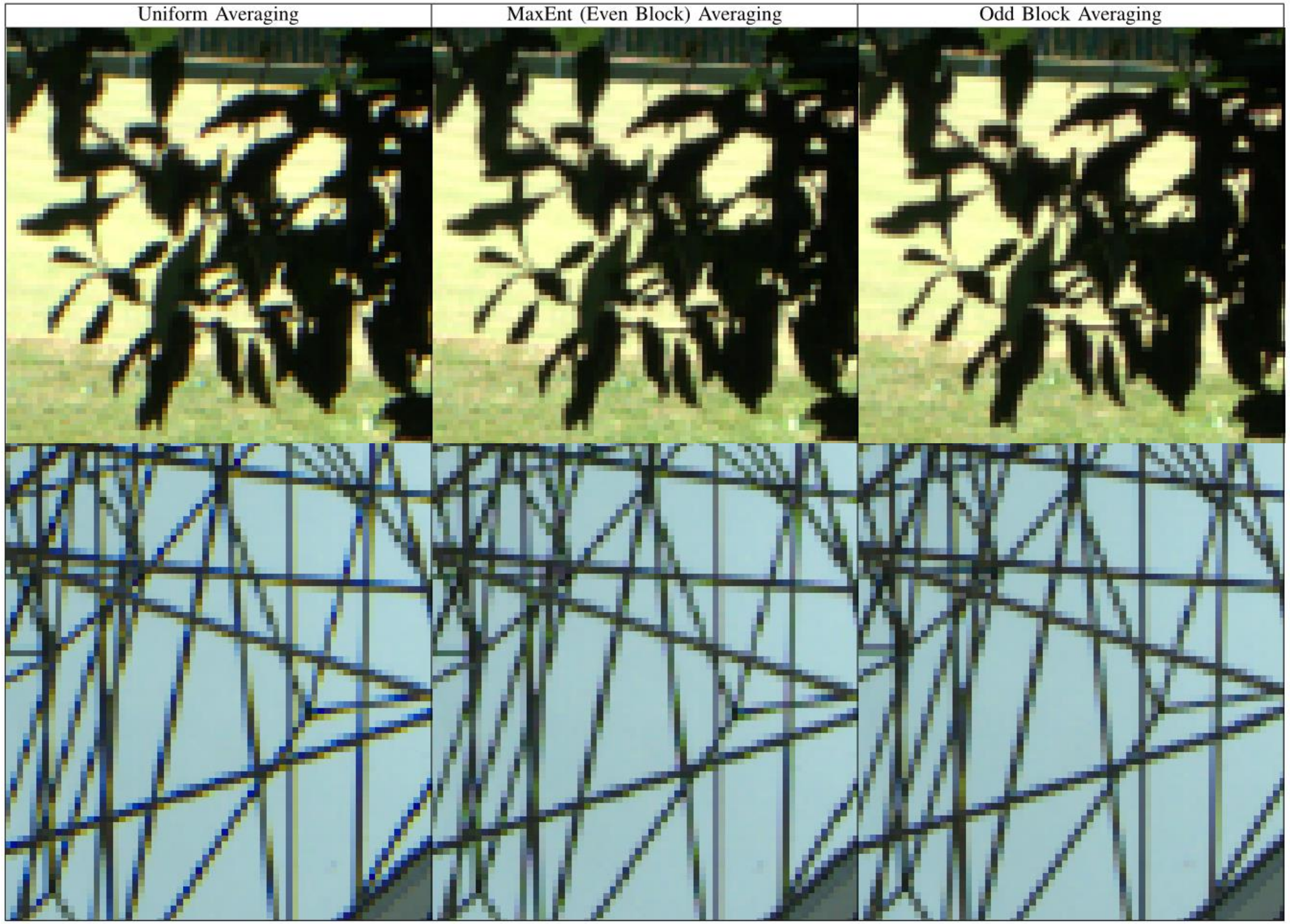

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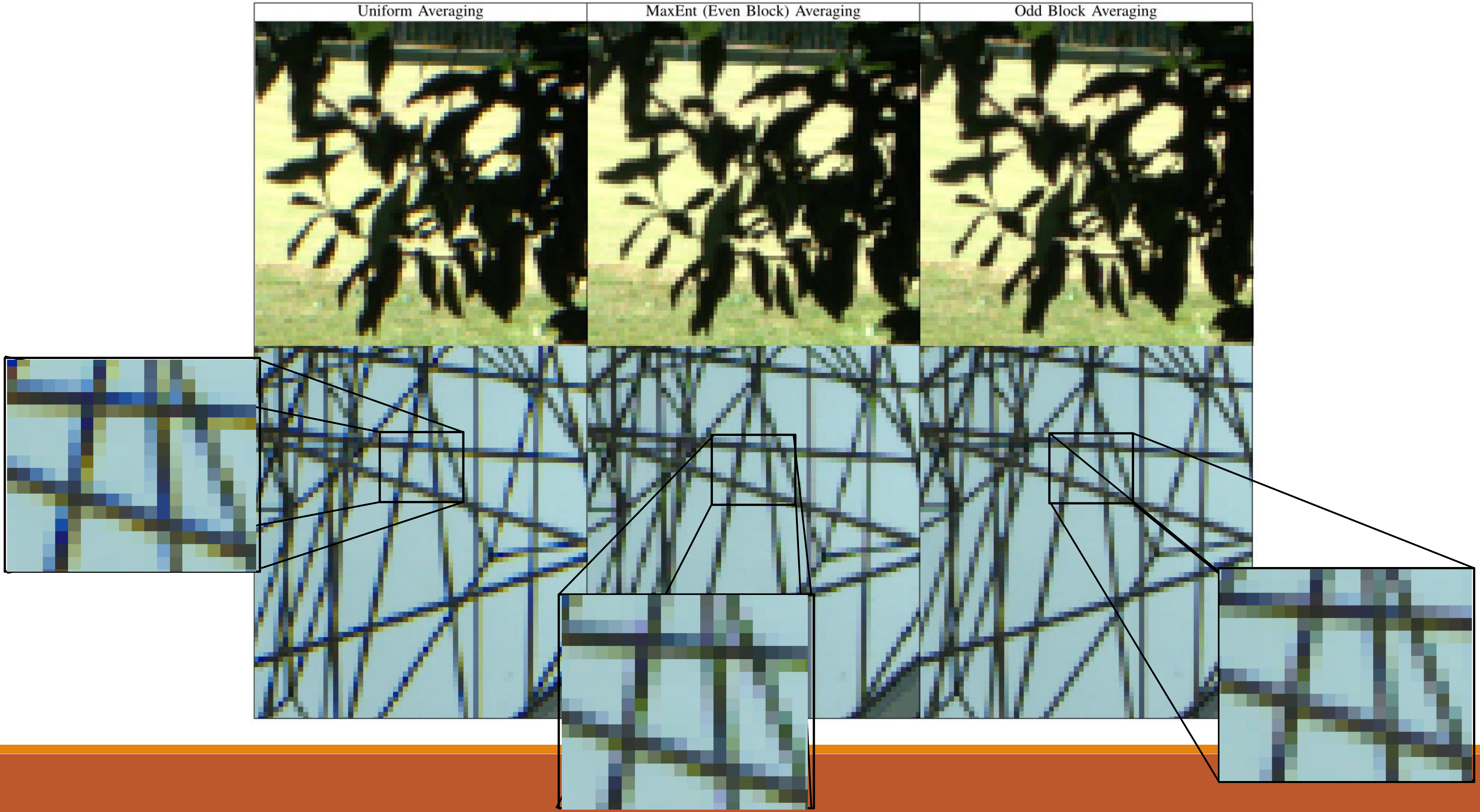

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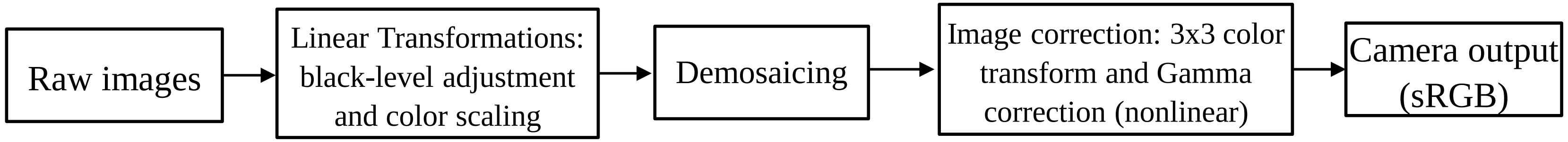

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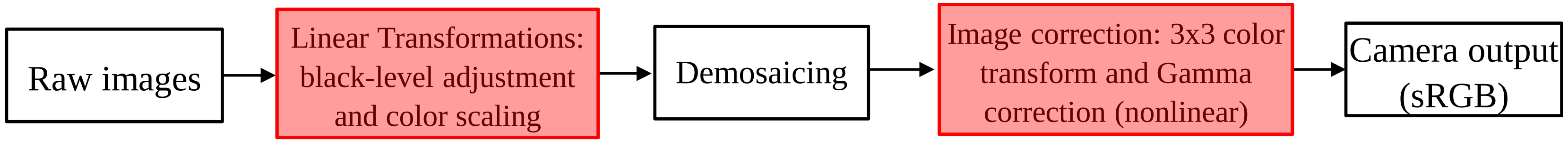

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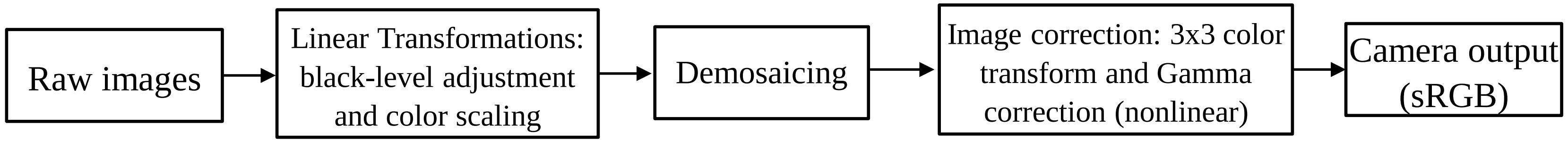

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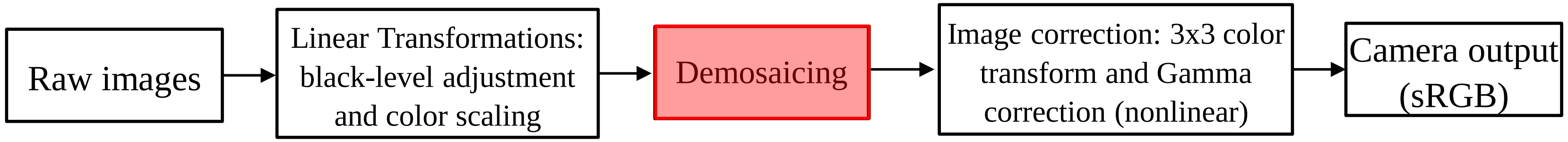

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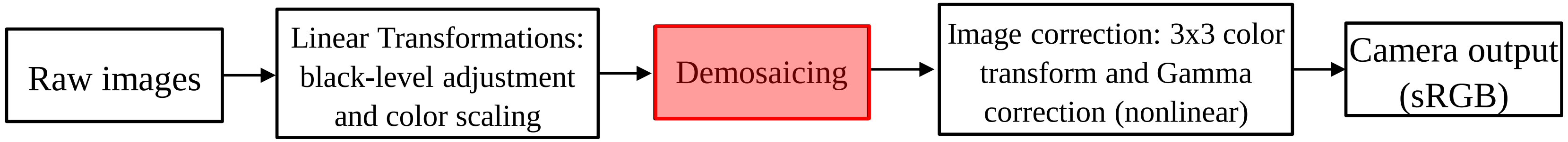

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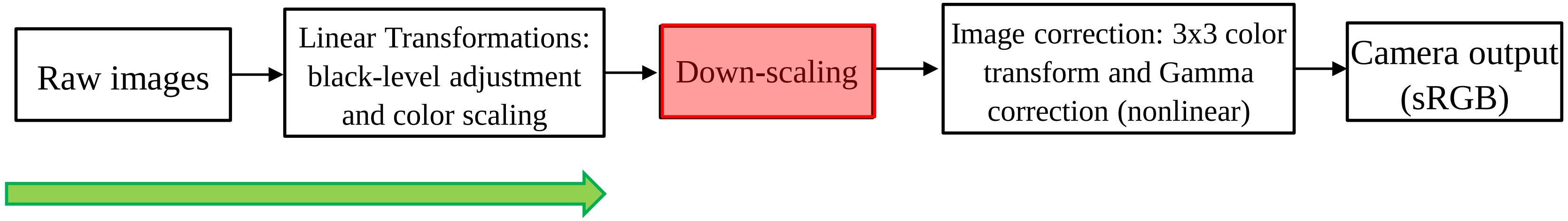

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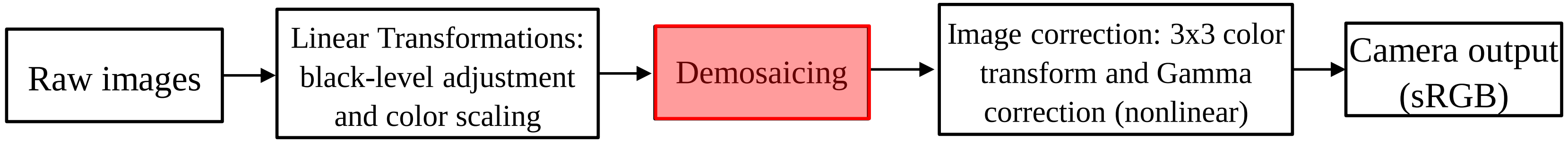

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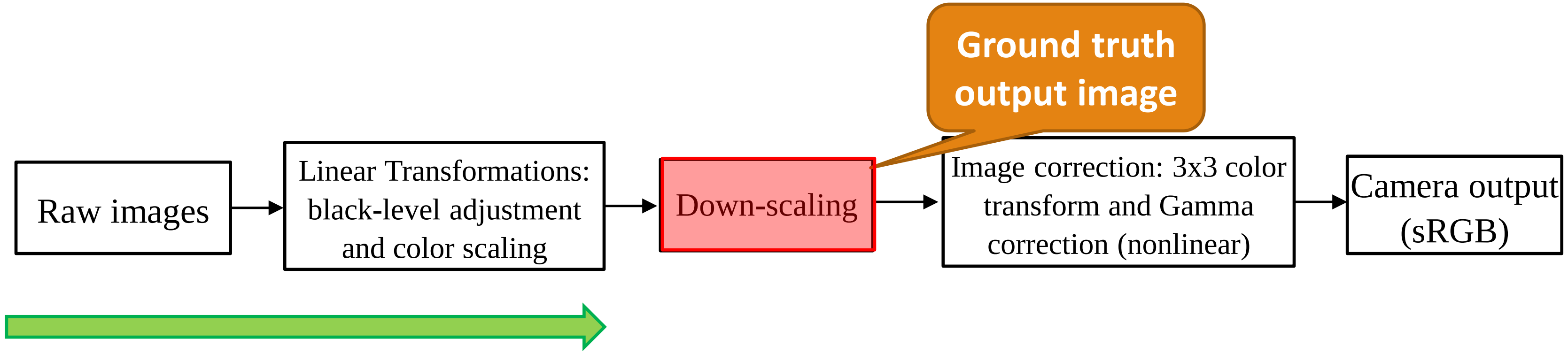

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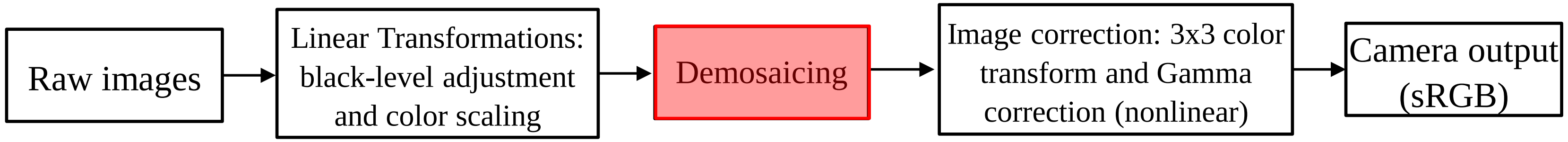

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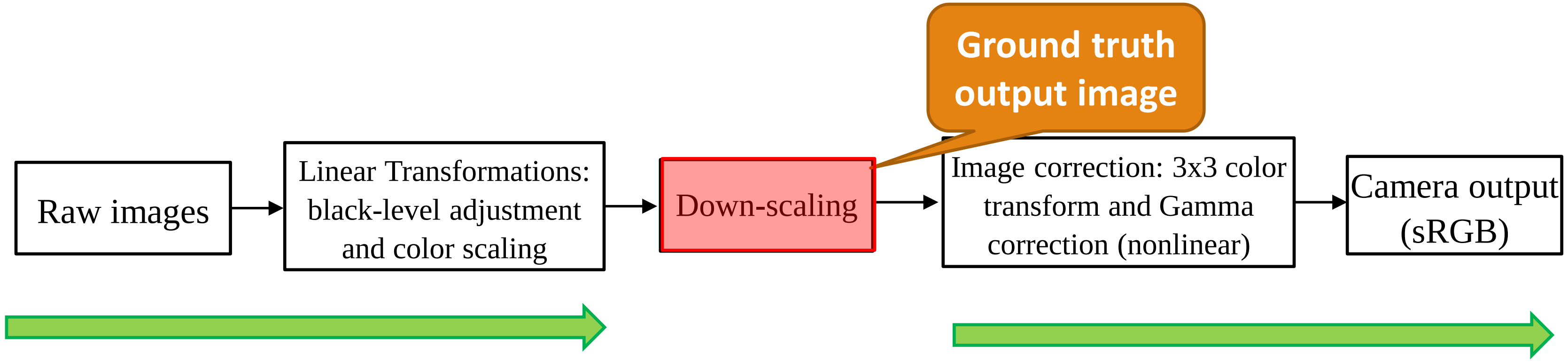

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$$\chi\left(y(x) + \eta_{\mathrm{p}}(y(x))\right) \sim \mathcal{P}(\chi y(x)), \quad \eta_{\mathrm{g}}(x) \sim \mathcal{N}(0, b),$$

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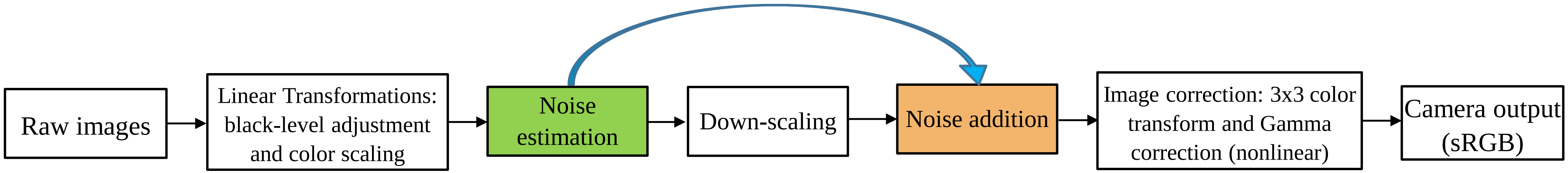

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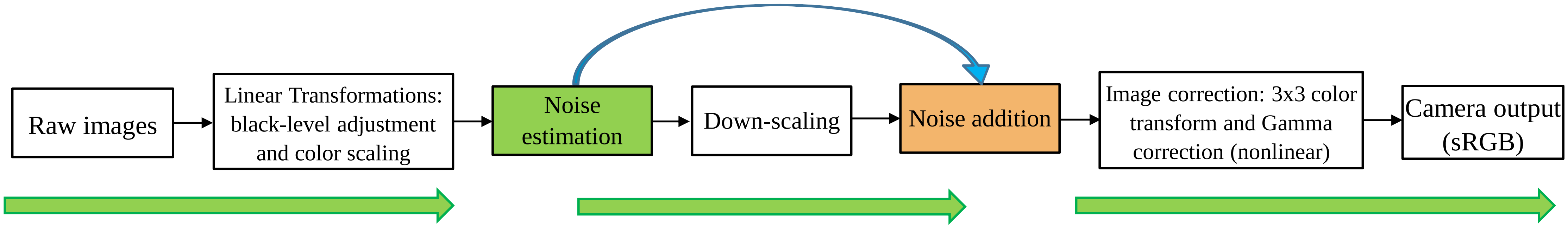

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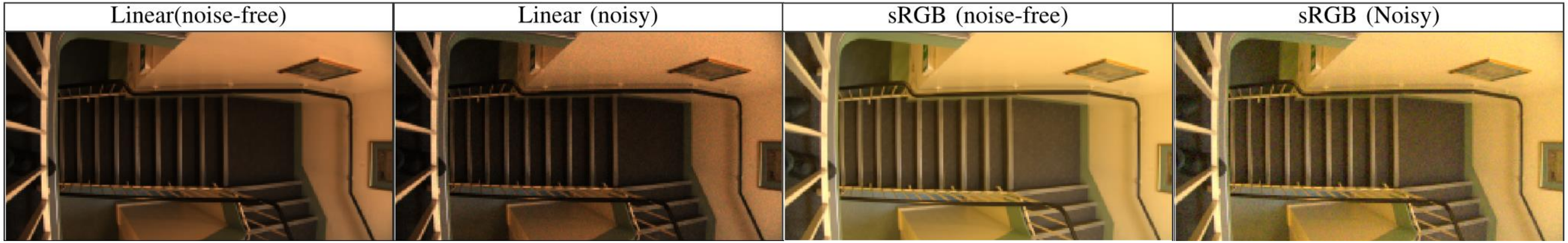

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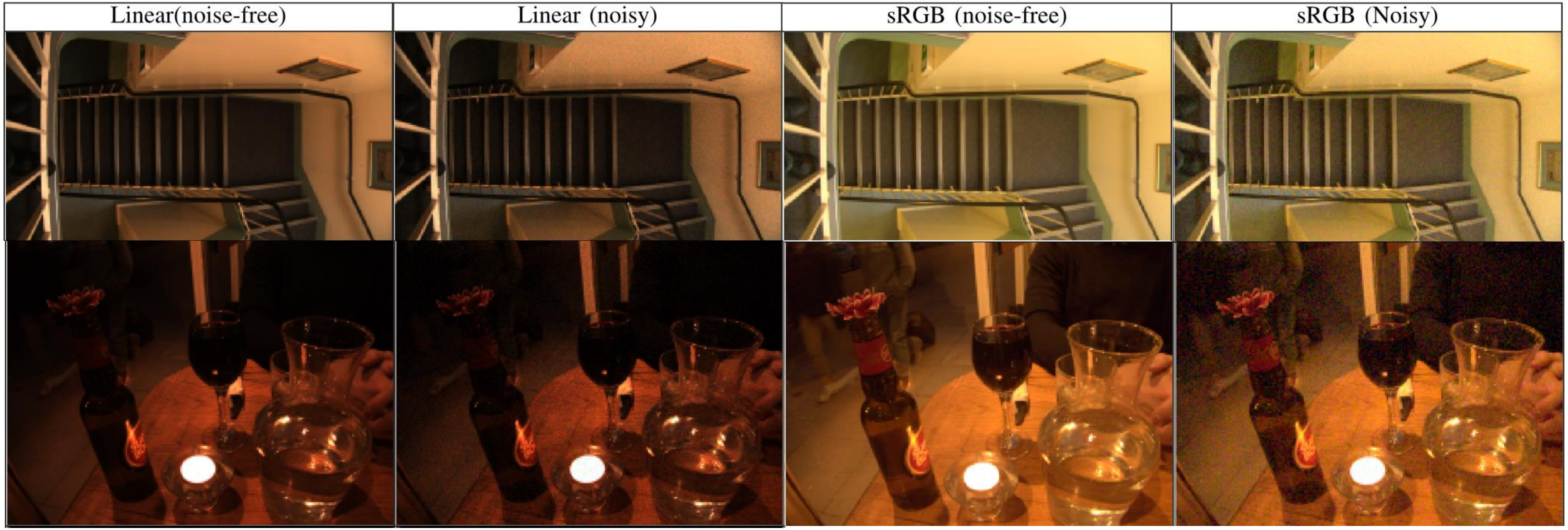


Samples of noise-addition to image

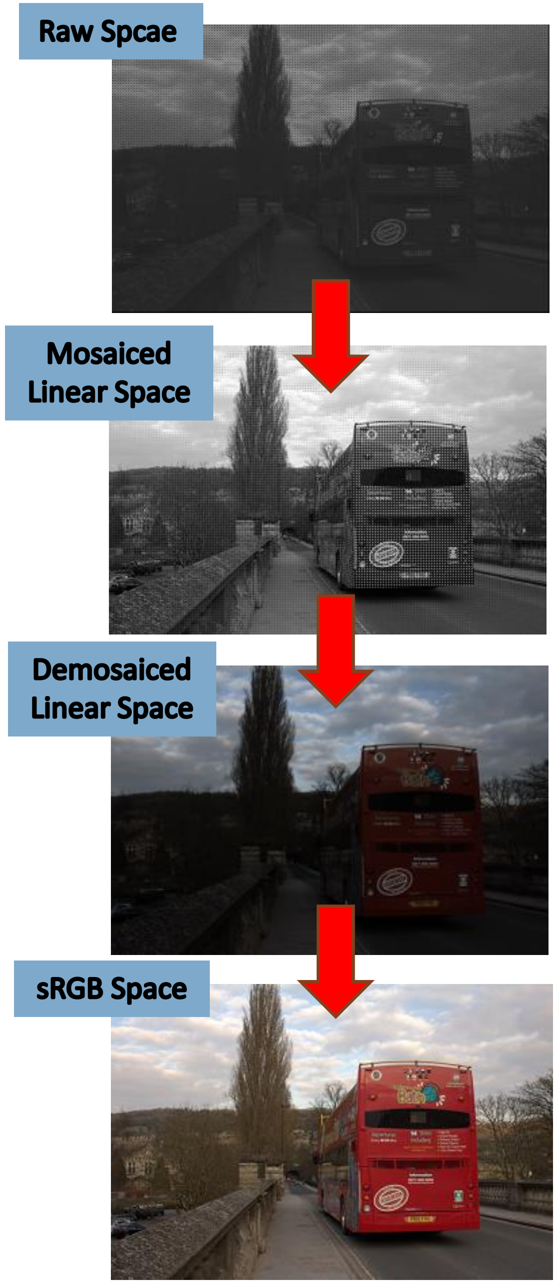
Linear(noise-free)	Linear (noisy)	sRGB (noise-free)	sRGB (Noisy)

Possible tasks

- We have developed these images

Raw images

- Among the above tasks we are mostly interested in doing the followings:
  - Demosaicing in linear light-space
  - Deniosing +demosaicing in linear light-spcae



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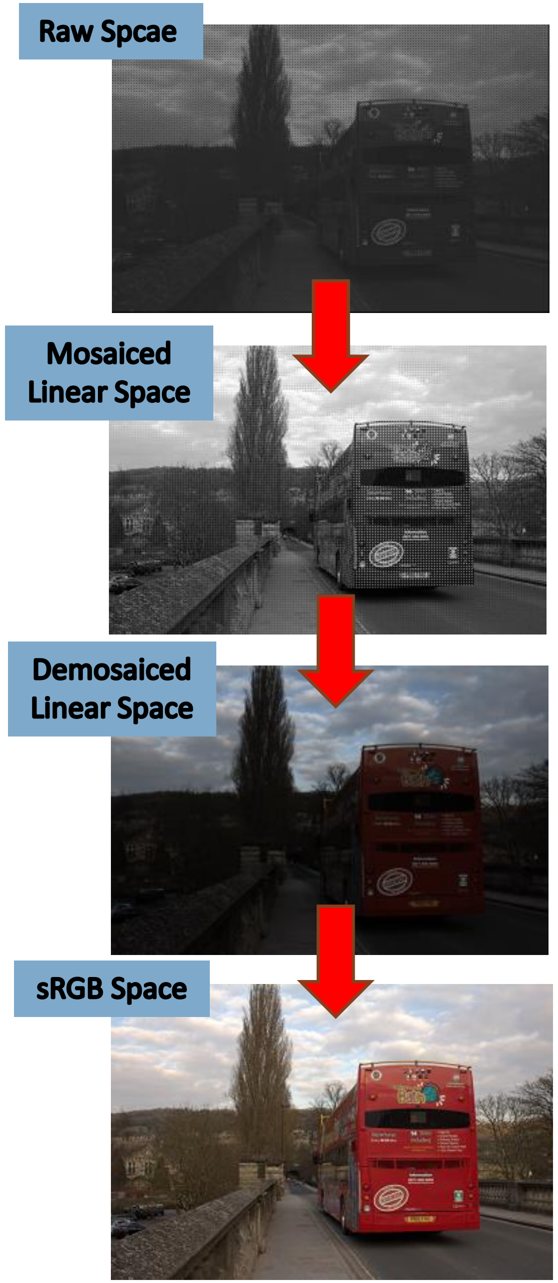

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Raw images → Noise-free-linear → Noise-free-sRGB

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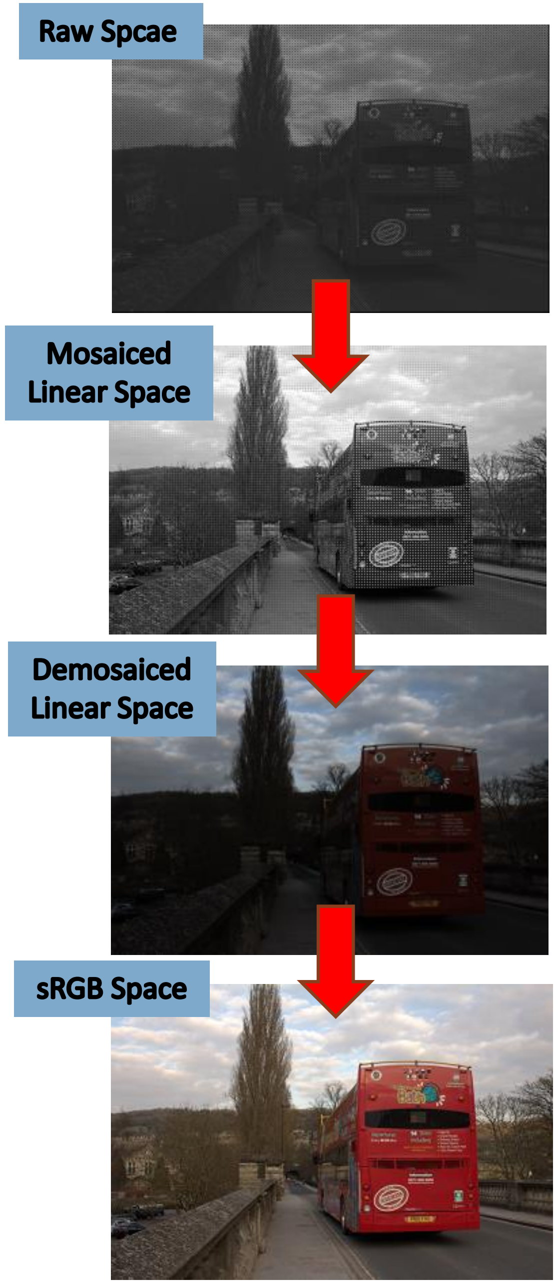

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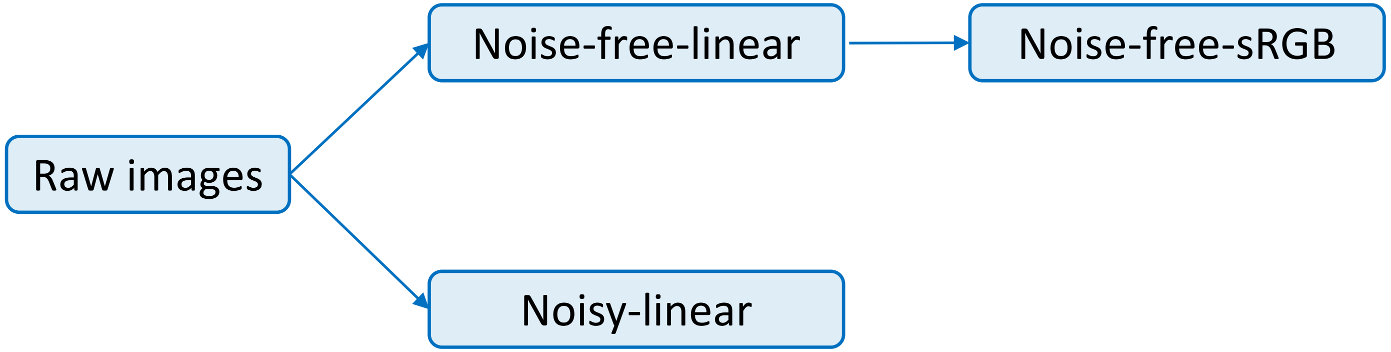

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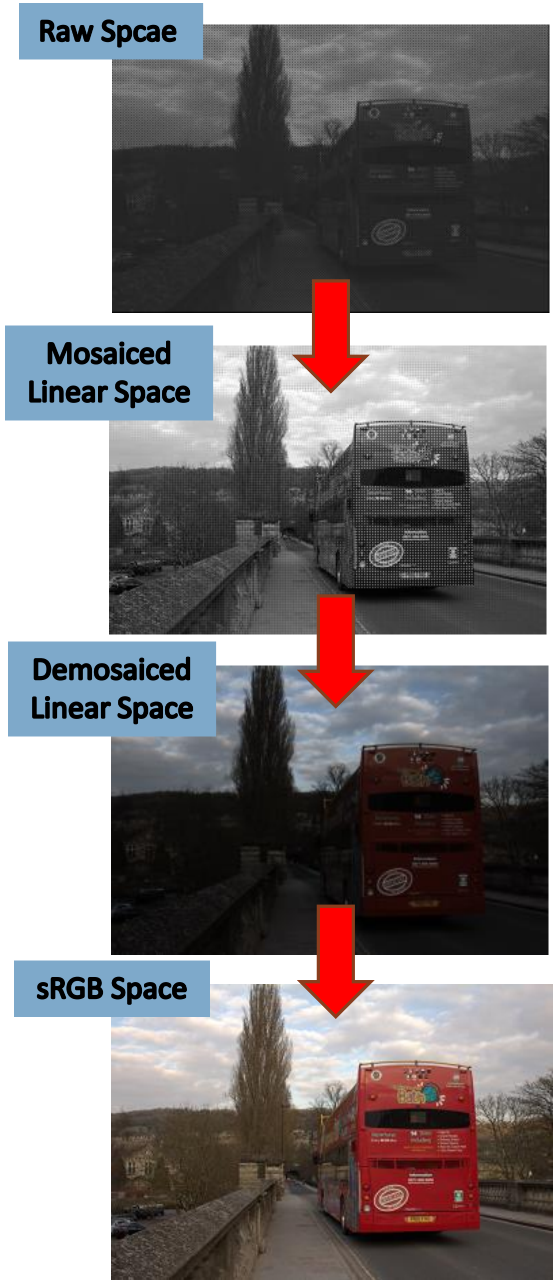

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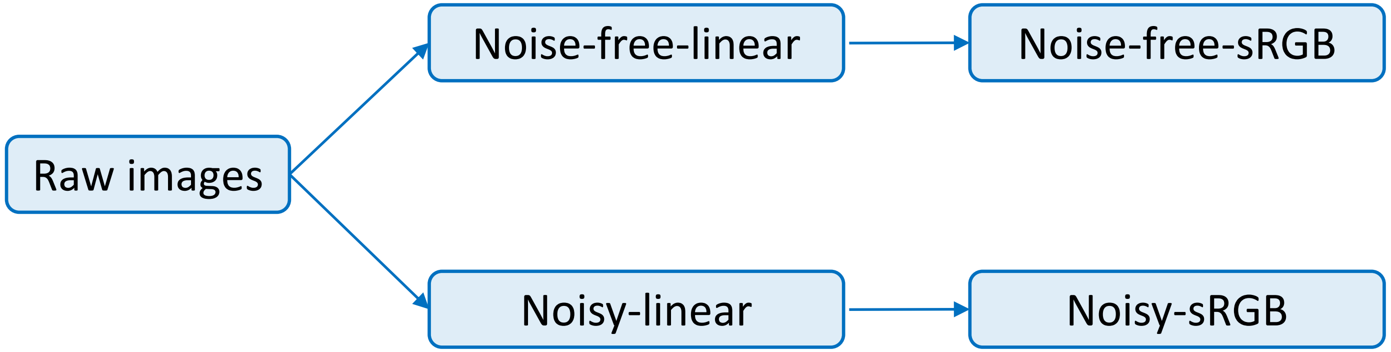

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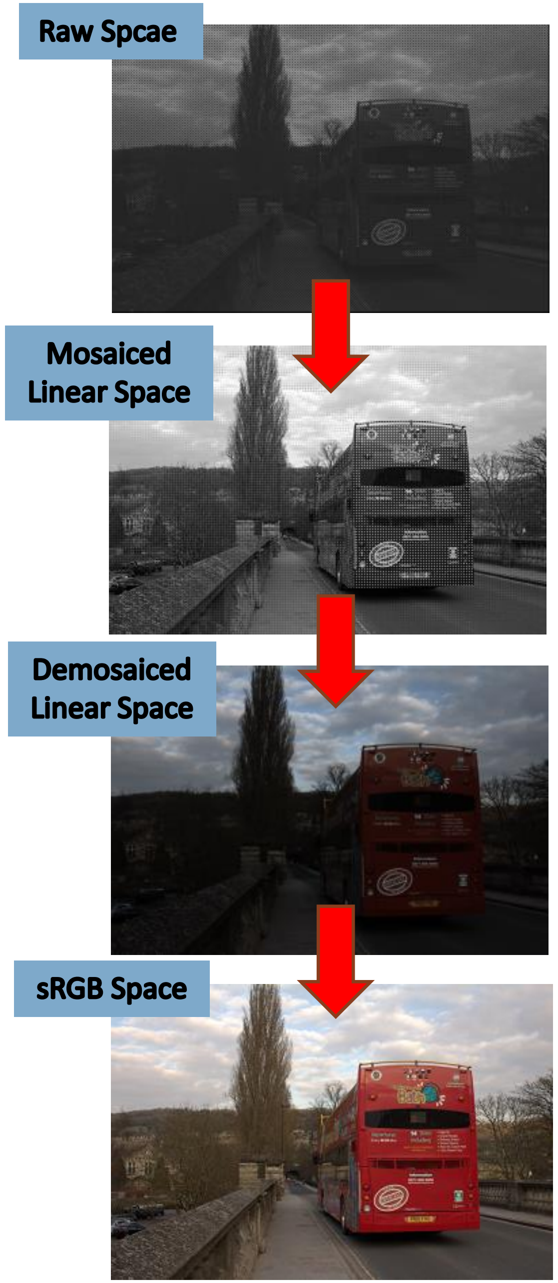
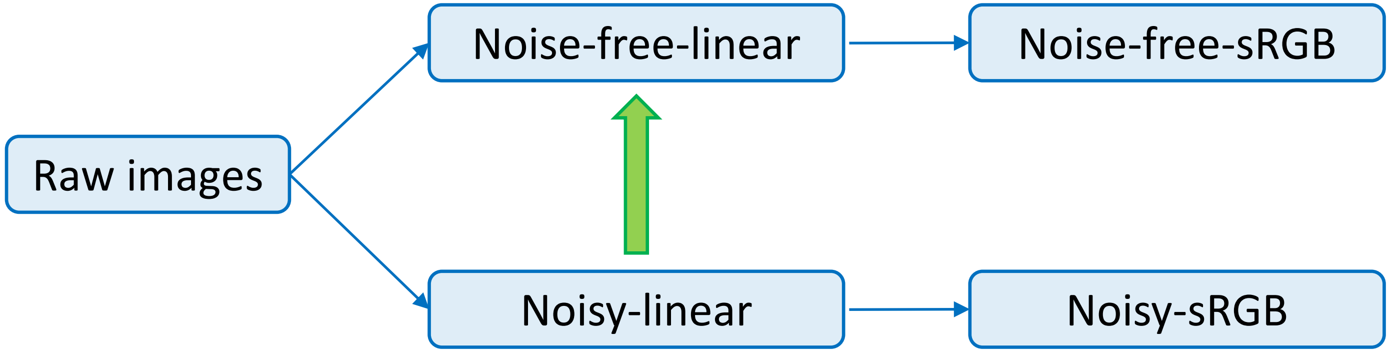


Possible tasks

- We have developed these images



- Among the above tasks we are mostly interested in doing the followings:
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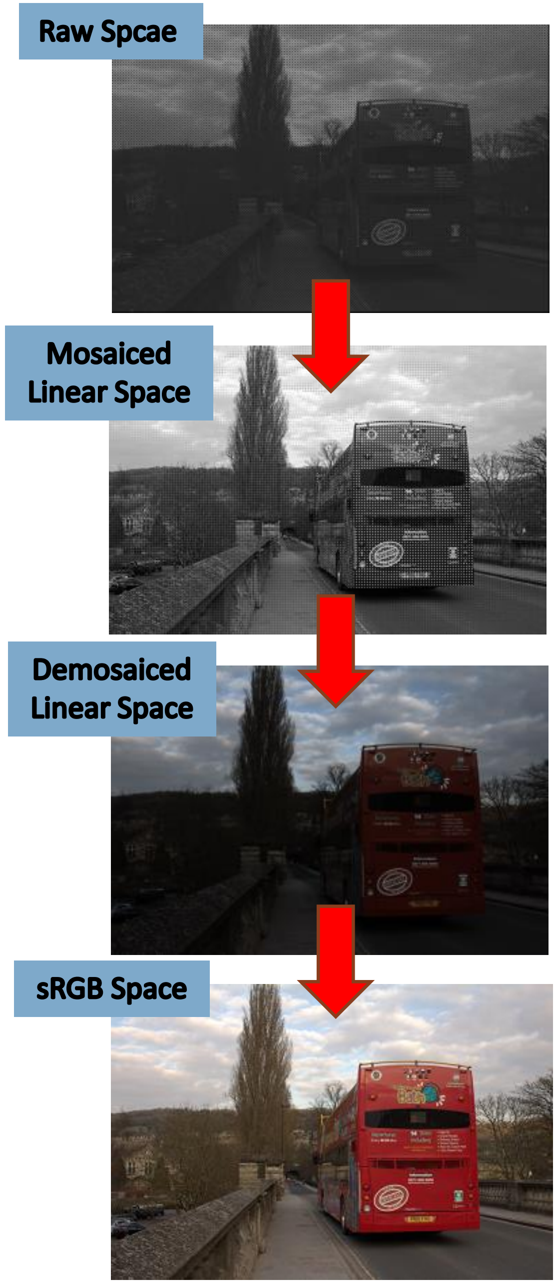

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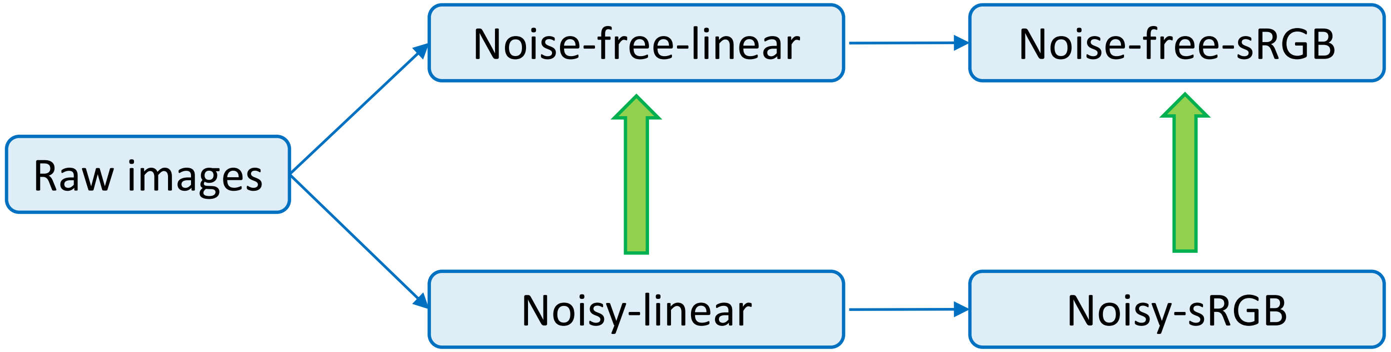

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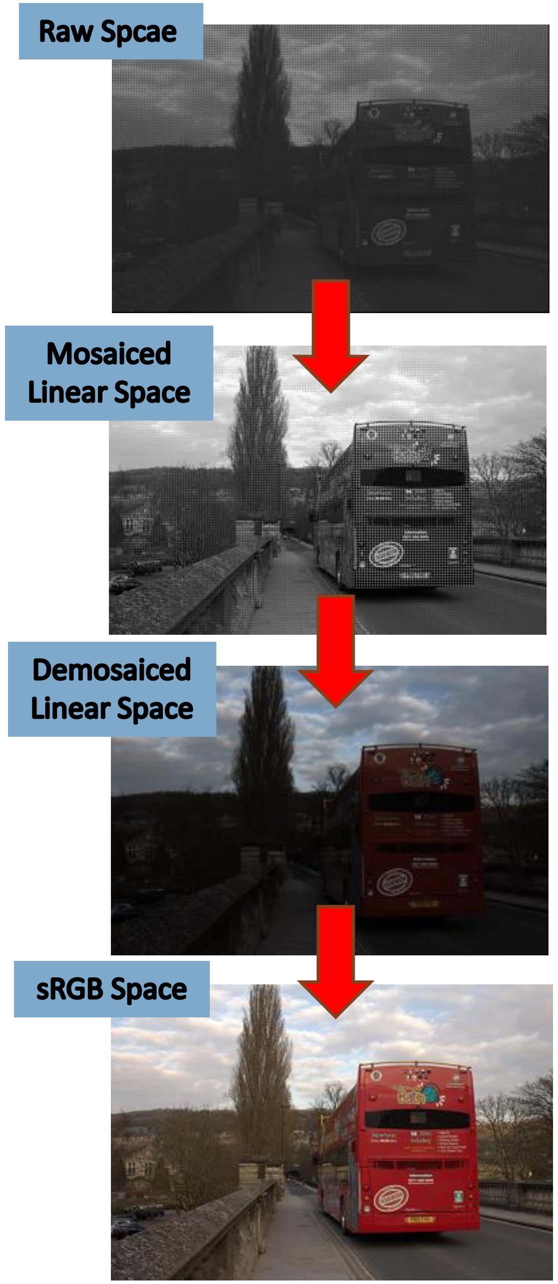
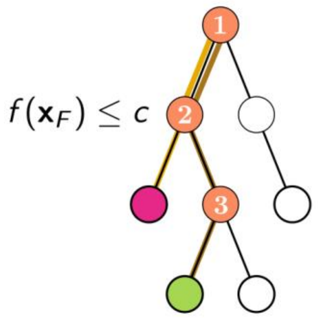
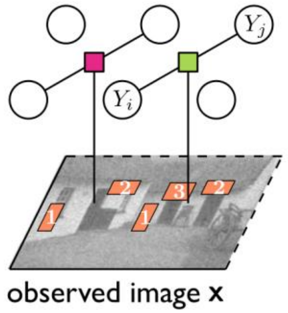


Regression tree field

- Combines **regression tress (Non-parametric)** and **Gaussian Random Fields**





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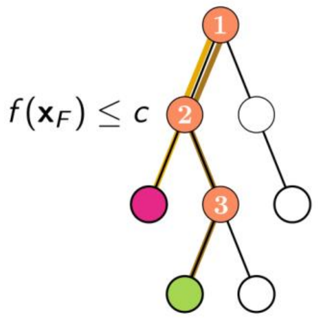
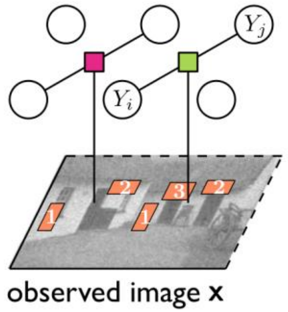




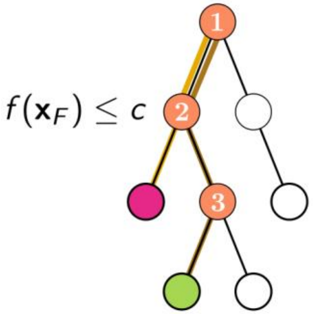
- Energy defined for each factor:

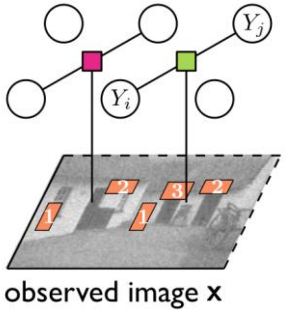
$$E(\mathbf{y}_F \mid \mathbf{x}_F) = \frac{1}{2}\mathbf{y}_F^{\mathsf{T}}\mathbf{Q}(\mathbf{x}_F)\mathbf{y}_F - \mathbf{y}^{\mathsf{T}}\mathbf{L}(\mathbf{x}_F)\mathbf{b}(\mathbf{x}_F)$$

  - Measure of the goodness of particular labelling given inputs, and parameters of the factor

Regression tree field

- Combines **regression tress (Non-parametric)** and **Gaussian Random Fields**



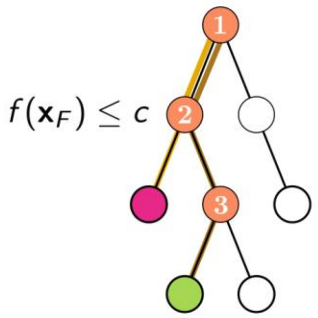


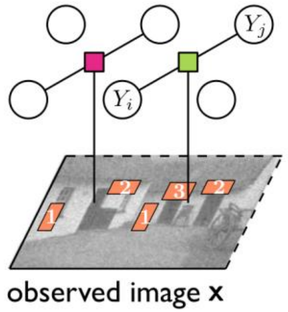
$$E(\mathbf{y}_F \mid \mathbf{x}_F) = \frac{1}{2}\mathbf{y}_F^T \mathbf{Q}(\mathbf{x}_F)\mathbf{y}_F - \mathbf{y}^T \mathbf{L}(\mathbf{x}_F)\mathbf{b}(\mathbf{x}_F)$$

- Energy defined for each factor:
  - Measure of the goodness of particular labelling given inputs, and parameters of the factor
  - Coefficients of are determined by the **regression tree**, or each leave stores set of parameters.

Regression tree field

- Combines **regression tress (Non-parametric)** and **Gaussian Random Fields**



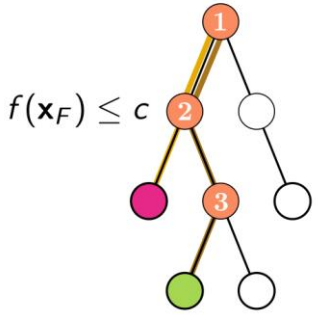


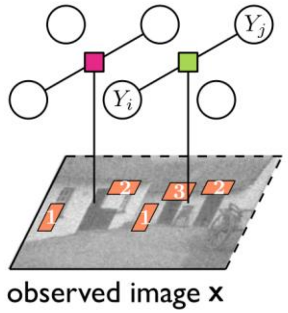
- Energy defined for each factor: $E(\mathbf{y}_F \mid \mathbf{x}_F) = \frac{1}{2}\mathbf{y}_F^{\mathsf{T}}\mathbf{Q}(\mathbf{x}_F)\mathbf{y}_F - \mathbf{y}^{\mathsf{T}}\mathbf{L}(\mathbf{x}_F)\mathbf{b}(\mathbf{x}_F)$
  - Measure of the goodness of particular labelling given inputs, and parameters of the factor
  - Coefficients of are determined by the **regression tree**, or each leave stores set of parameters.
- **Inference**:

$$p(\mathbf{y} \mid \mathbf{x}; \mathbf{w}) \propto \exp[-E(\mathbf{y} \mid \mathbf{x}; \mathbf{w})] \quad \Rightarrow \quad \hat{\mathbf{y}}(\mathbf{x}) = \operatorname{argmax}_{\mathbf{y}}\, p(\mathbf{y} \mid \mathbf{x}) = \boldsymbol{\mu} = [\mathbf{Q}(\mathbf{x}; \mathbf{w})]^{-1}\mathbf{l}(\mathbf{x}; \mathbf{w})$$

Regression tree field

- Combines **regression tress (Non-parametric)** and **Gaussian Random Fields**





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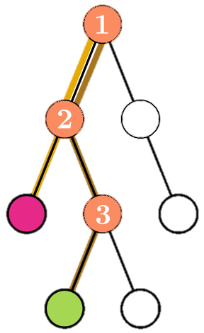
  - Measure of the goodness of particular labelling given inputs, and parameters of the factor
  - Coefficients of are determined by the **regression tree**, or each leave stores set of parameters.
- **Inference**:
- **Training**: Jointly choosing the structure of the tree, and parameters of at leaves such that minimizes the empirical risk, in greedy way:

$$p(\mathbf{y} \mid \mathbf{x}; \mathbf{w}) \propto \exp[-E(\mathbf{y} \mid \mathbf{x}; \mathbf{w})] \quad \Longrightarrow \quad \hat{\mathbf{y}}(\mathbf{x}) = \operatorname{argmax}_{\mathbf{y}}\, p(\mathbf{y} \mid \mathbf{x}) = \boldsymbol{\mu} = [\mathbf{Q}(\mathbf{x}; \mathbf{w})]^{-1}\mathbf{l}(\mathbf{x}; \mathbf{w})$$

$$\frac{1}{N}\sum_{i}^{N} \ell(\hat{\mathbf{y}}(\mathbf{x}^{(i)}; \mathbf{w}), \mathbf{y}^{(i)}) \approx \mathbb{E}_{p(\mathbf{x},\mathbf{y})}\left[\ell(\hat{\mathbf{y}}(\mathbf{x}; \mathbf{w}), \mathbf{y})\right]$$

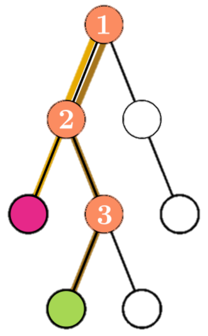
Regression tree fields, for demosaicing



[1] RFS filters: http://www.robots.ox.ac.uk/~vgg/research/texclass/filters.html

Regression tree fields, for demosaicing

- **Tree Feature checks**,
  - A preliminary bilinear interpolation



Regression tree fields, for demosaicing

- **Tree Feature checks**,
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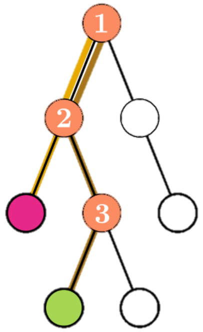
  - RFS filters [1] which act like derivatives in different directions, with various scales



Regression tree fields, for demosaicing

- **Tree Feature checks**,
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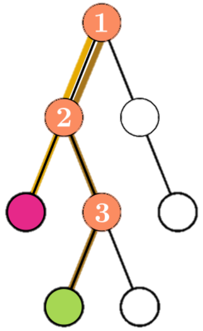
  - RFS filters [1] which act like derivatives in different directions, with various scales
- Quadratic energy basis vectors,
  - Set of neightbouring pixels,



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Regression tree fields, for demosaicing

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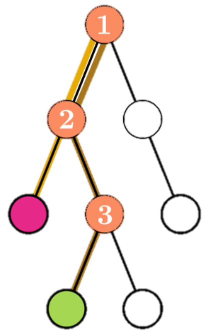
  - Set of neightbouring pixels,
  - RFS filter responses



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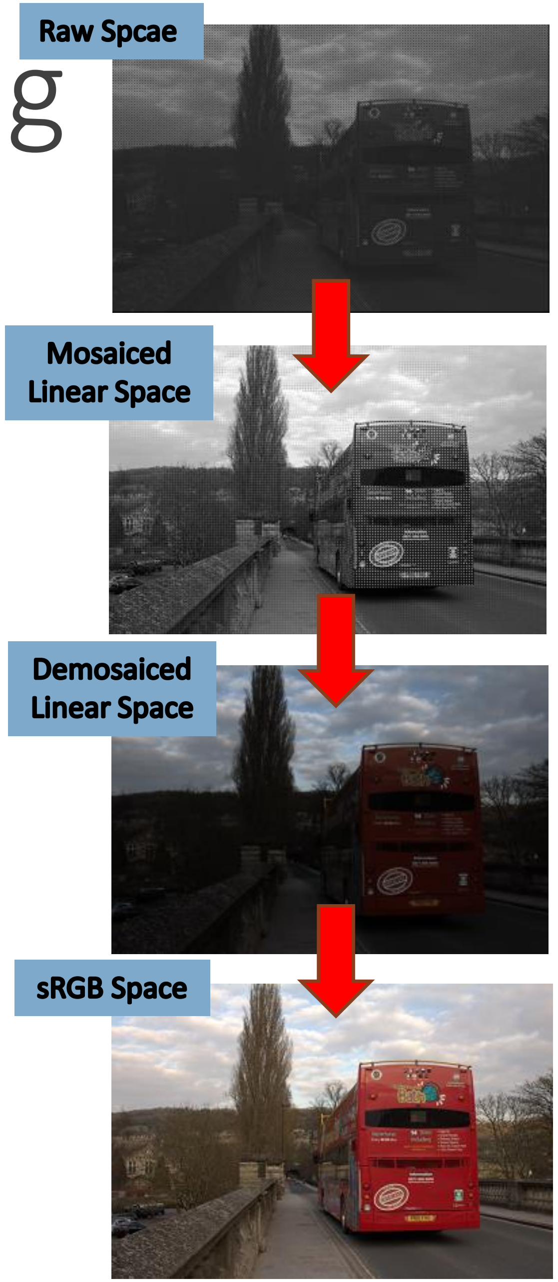
Regression tree fields, for demosaicing

- The generalized loss function,



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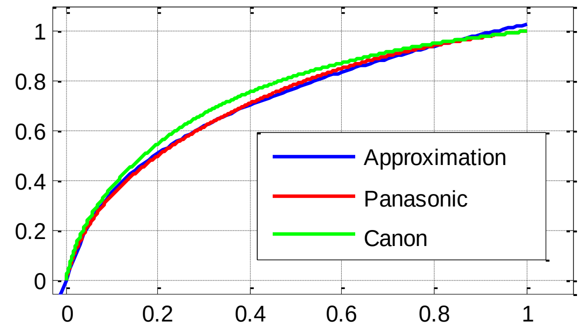
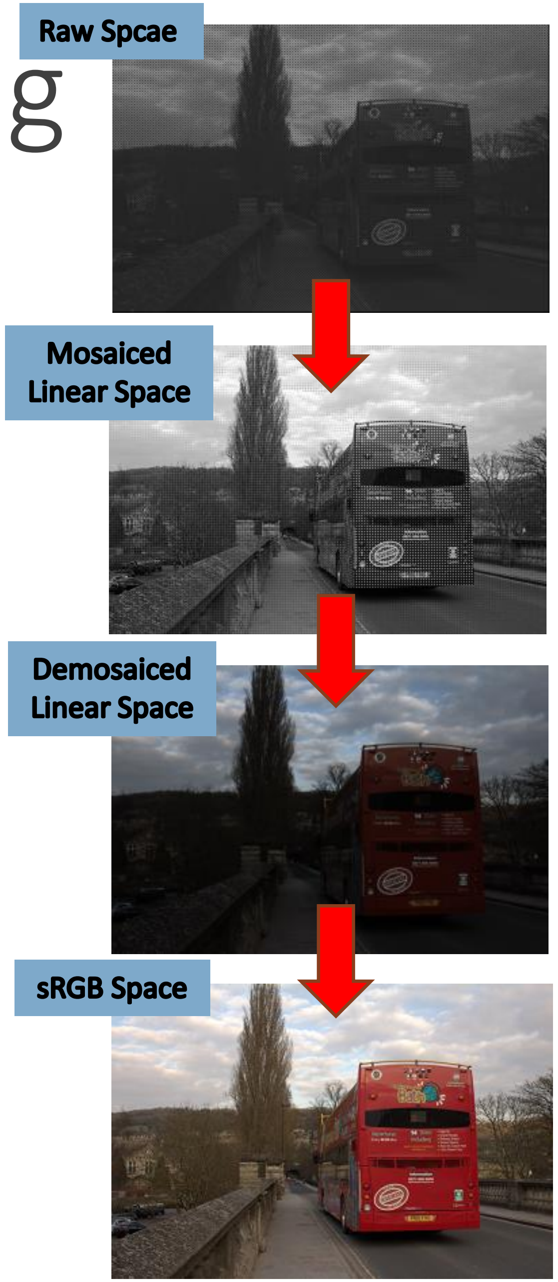
Regression tree fields, for demosaicing

- The generalized loss function,
  - An approximate camera pipeline, from linear-space, to sRGB space, which is differentiable
    - An analytic approximation for gamma transform





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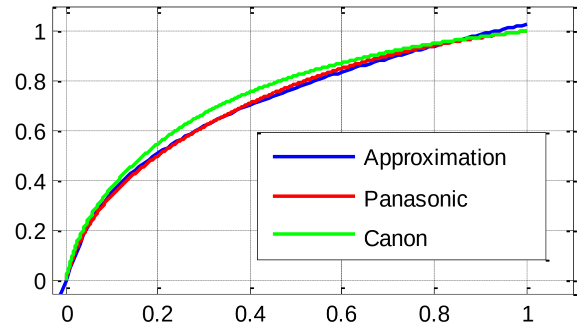

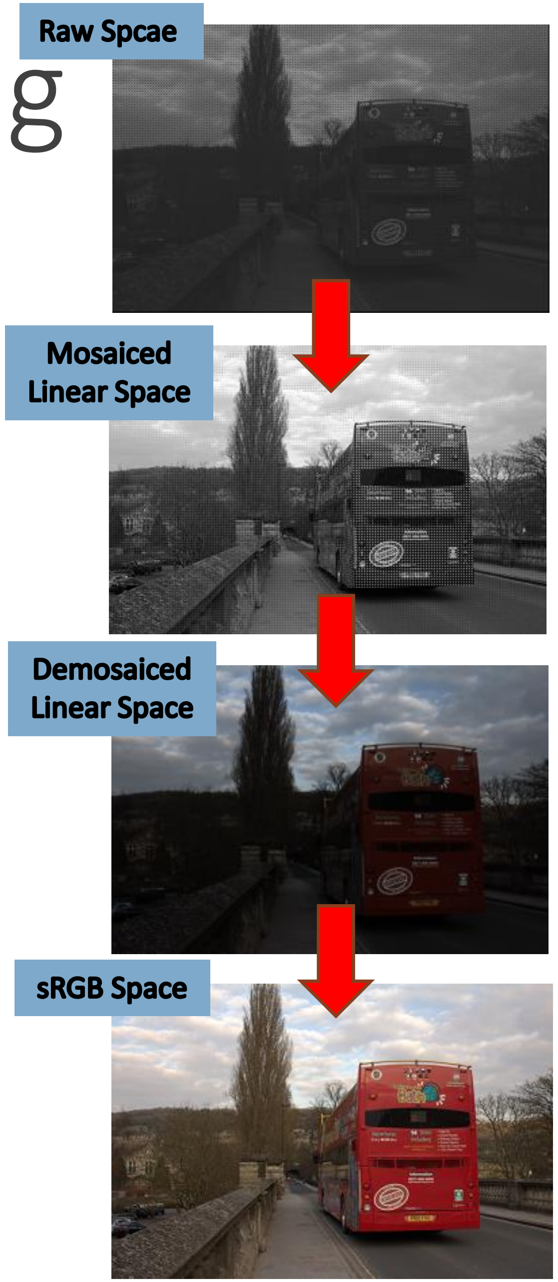

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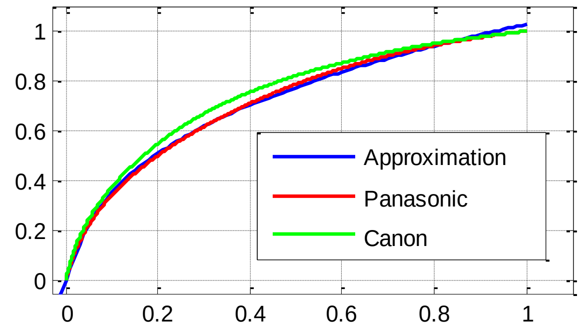
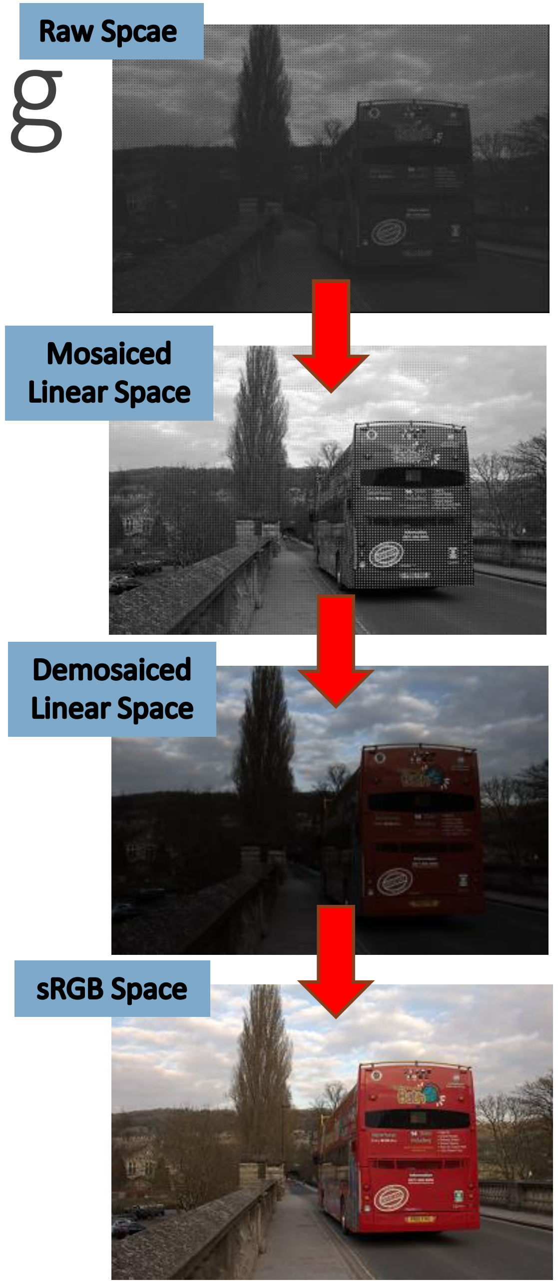
$$c_{\mathrm{MSE}}(\mathbf{I}, \tilde{\mathbf{I}}) = \sum_{i=\{R,G,B\}} \sum_{x,y} \left(I^i_{x,y} - \tilde{I}^i_{x,y} \right)^2.$$





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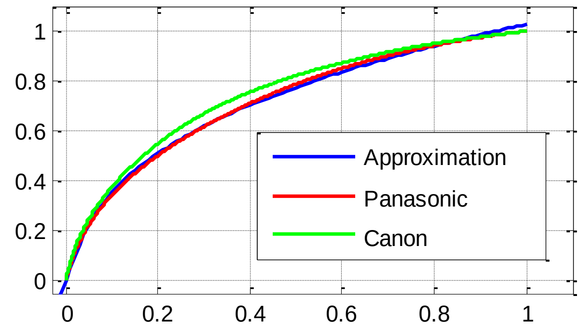
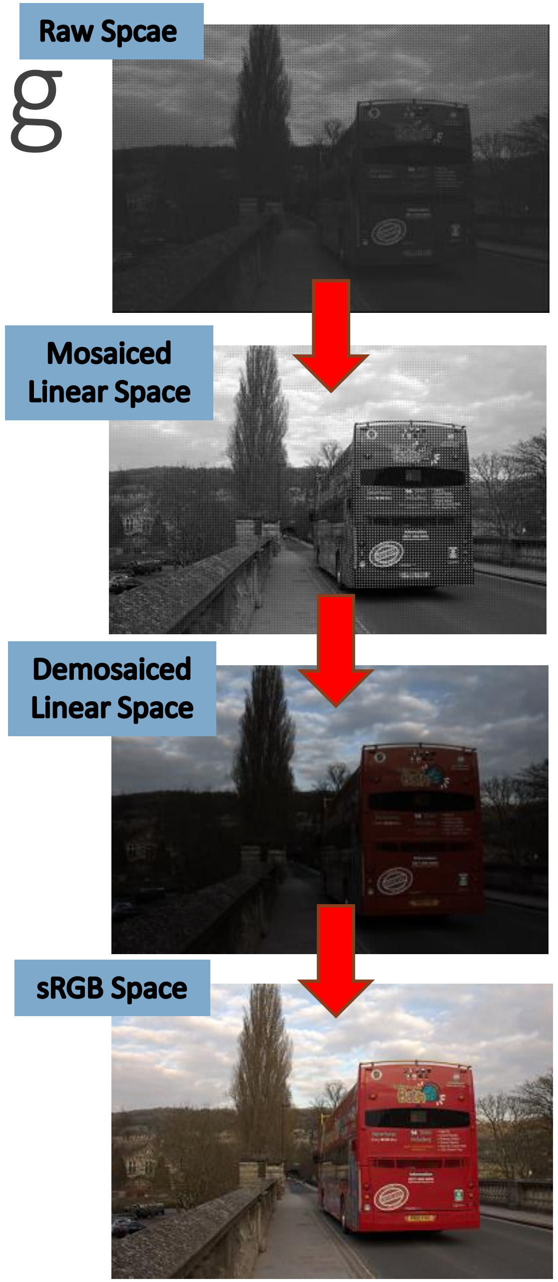


$$c_{\text{MSE}}(\mathbf{I},\tilde{\mathbf{I}}) = \sum_{i=\{R,G,B\}} \sum_{x,y} \left(I^i_{x,y} - \tilde{I}^i_{x,y}\right)^2.$$

$$f : \mathbf{L} \to \mathbf{I} \implies c_{\text{G-MSE}}(\mathbf{L},\tilde{\mathbf{L}}) \triangleq (c_{\text{MSE}} \circ f)(\mathbf{L},\tilde{\mathbf{L}}) = \sum_{i=\{R,G,B\}} \sum_{x,y} \left(f(L^i_{x,y}) - f(\tilde{L}^i_{x,y})\right)^2$$



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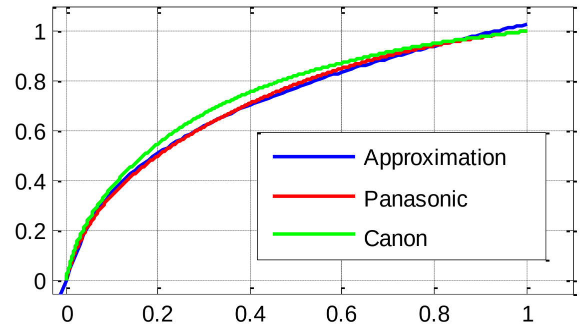

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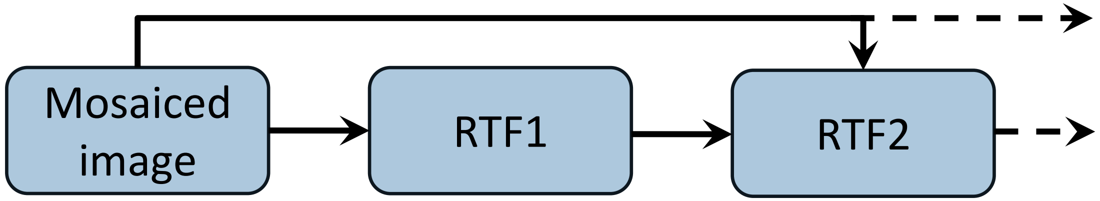
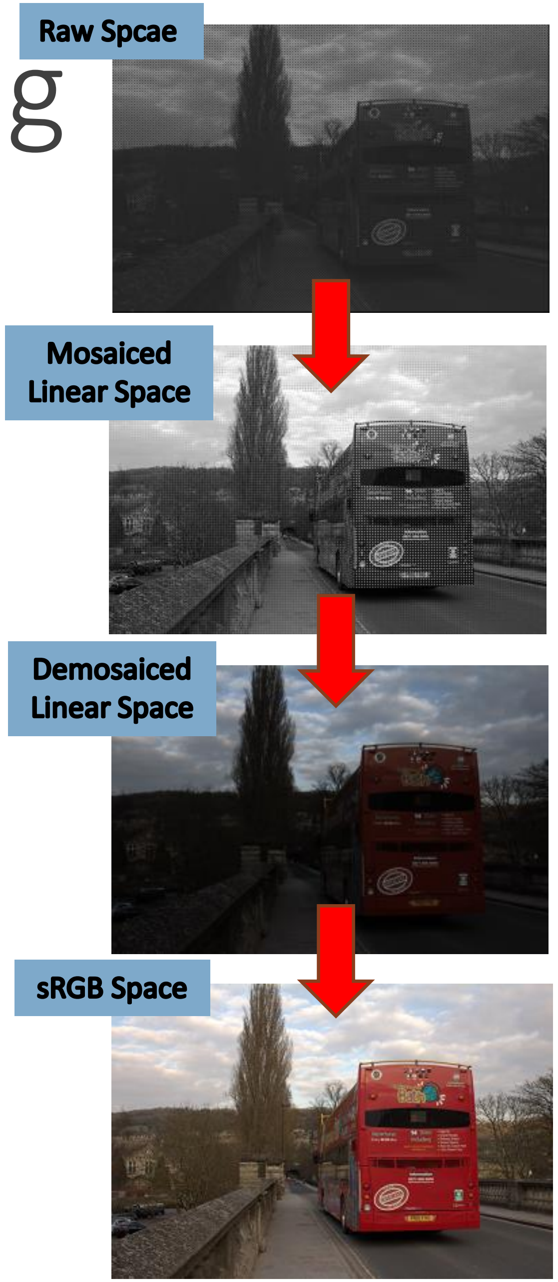
- Stacking RTFs,





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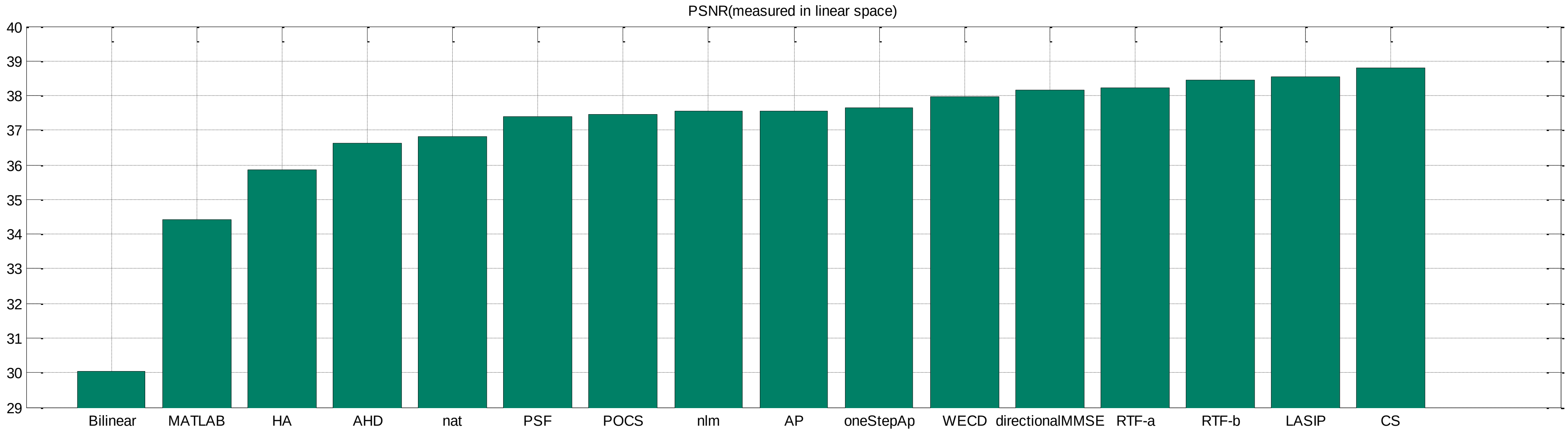
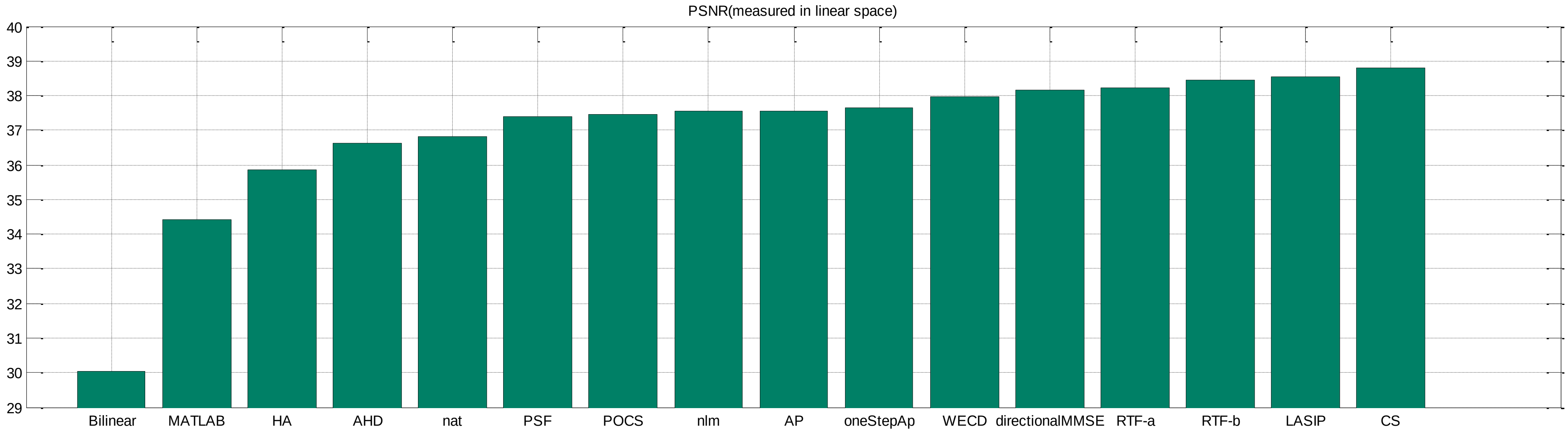
Experiments(1)

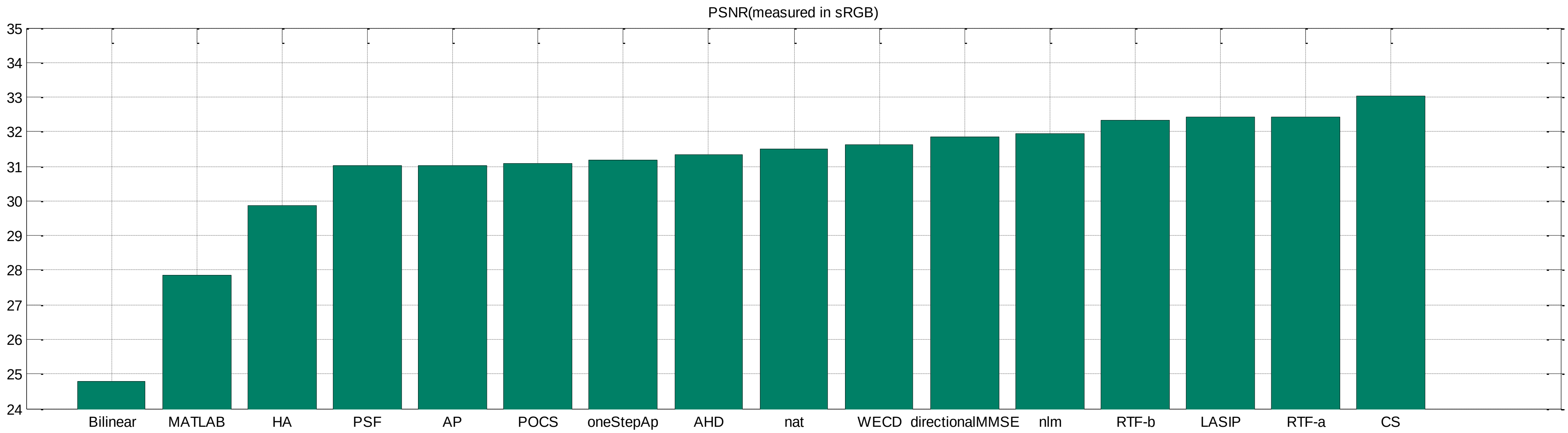


Experiments(1)

- **Demosaicing, in linear-space, without noise:**



Experiments(2)



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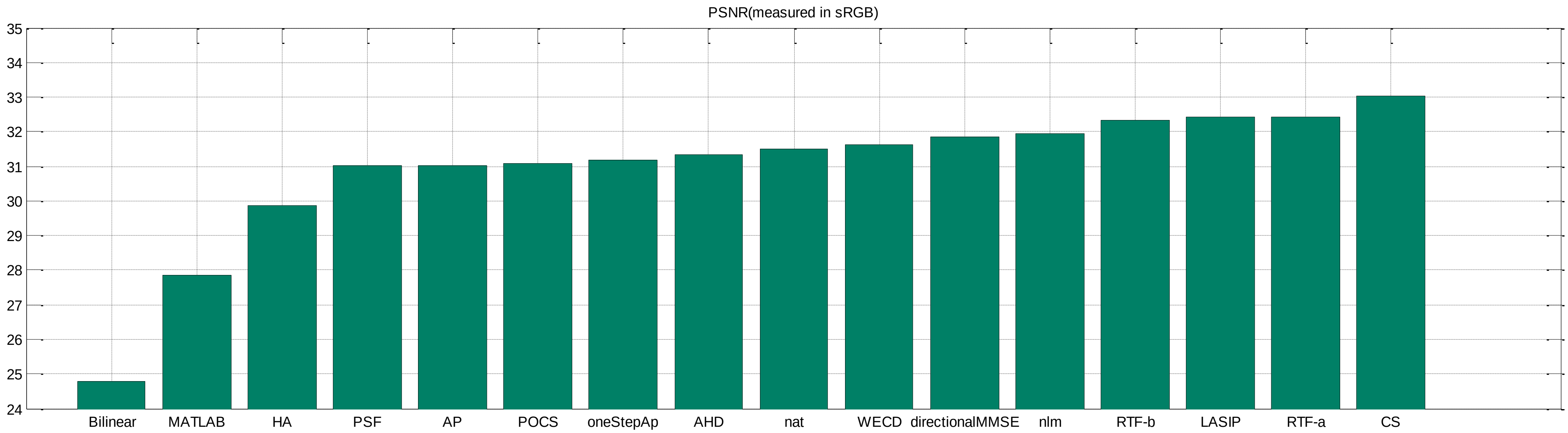

Some samples

NAT: Non-Local Adaptive Thresholding:
NLM: Non-Local Means

Some samples

Ground truth Bilinear CS RTF

NAT: Non-Local Adaptive Thresholding:
NLM: Non-Local Means

Some samples

NAT: Non-Local Adaptive Thresholding:
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Some samples

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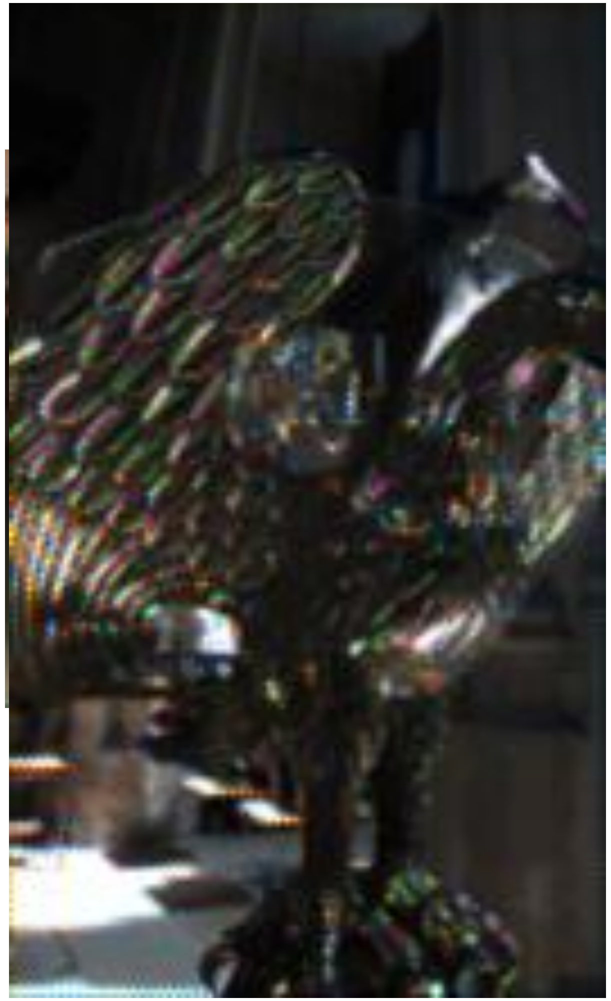
Some samples


Ground truth


Bilinear


CS


RTF

Image Margins




NAT: Non-Local Adaptive Thresholding:
NLM: Non-Local Means

Image Margins

- Not a considerable margin in RTF outputs

NAT: Non-Local Adaptive Thresholding:
NLM: Non-Local Means

Image Margins

- Not a considerable margin in RTF outputs

NAT

NLM

OneStepAP

RTF

NAT: Non-Local Adaptive Thresholding:
NLM: Non-Local Means

And more to go ….

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- RTF with the generalized loss function

And more to go ....

- RTF with the generalized loss function
- Full denoising-demosiacing experiments

And more to go ….

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And more to go ….

- RTF with the generalized loss function
- Full denoising-demosiacing experiments
- Other CFA patterns: Fuji-Xtrans pattern
- **Further work?!**