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COLOR AFFINE SUBSPACE PURSUIT FOR COLOR ARTIFACT REMOVAL

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Outline

- Background
- Conventional method
- Purpose
- Proposed method
- Experimental results
- Conclusion

Background（Image restoration based on optimization ）

Noise

Blur

Low resolution

Desired image

Background（Image restoration based on optimization ）

Image restoration →

Noise　Blur　Low resolution　Estimated image　Desired image

Image restoration based on optimization

Data-fidelity　Regularization

$$\arg\min_{\mathbf{x}} \underbrace{\frac{1}{2}\|\boldsymbol{\Phi}\mathbf{x}-\mathbf{y}\|_2^2}_{\text{Data-fidelity}} + \underbrace{f(\mathbf{x})}_{\text{Regularization}} \quad \cdots (1)$$

- $\boldsymbol{\Phi}$ Degradation process
- $\mathbf{x}$ Estimated image
- $\mathbf{y}$ Observed image

A suitable model of a prior for the desired image is important to estimate a clean image

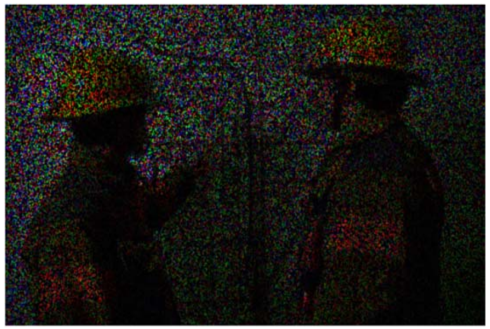
Background（Problems of Conventional regularization）

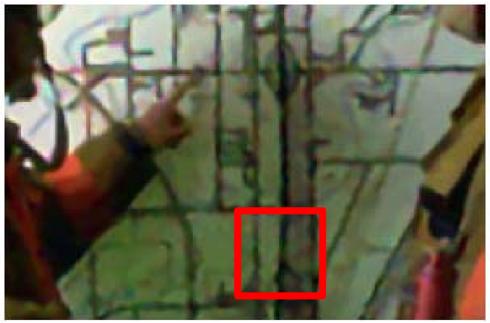
Data-fidelity Regularizer

$$\underset{\mathbf{x}}{\arg\min} \underbrace{\frac{1}{2}\|\boldsymbol{\Phi}\mathbf{x}-\mathbf{y}\|_2^2}_{\text{Data-fidelity}} + \underbrace{f(\mathbf{x})}_{\text{Regularizer}} \cdots (1)$$

- **Smooth region**
  - **-Total Variation (TV) [1]**
- **Texture region**
  - **-K-SVD [2]**
- **Periodic pattern texture region**
  - **- Structure-tensor TV (STV) [3]**
  - **- Nonlocal STV [4]**

Compression sensing [4 Chierchia+, TIP2014]





Color artifact arises

Our purpose : design efficient regularizer for color artifact removal

[1] Blomgren+, TIP1998 [2] Aharon+,TSP2006 [3] Lefkimmiatis,SIAM J.Imaging Sci.,2015.

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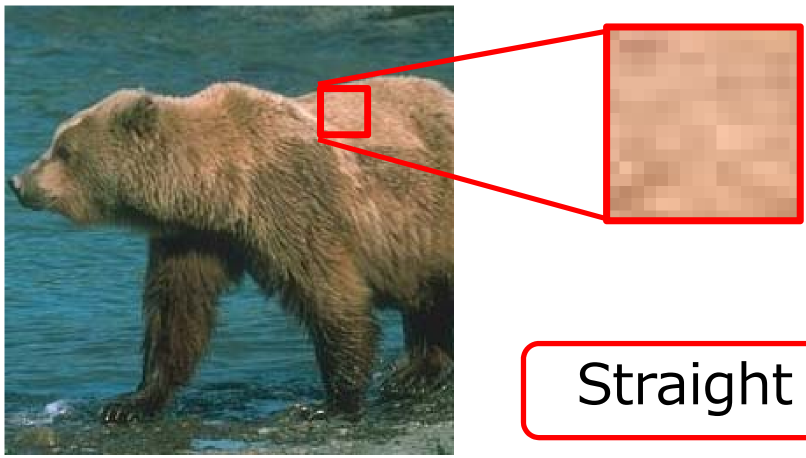
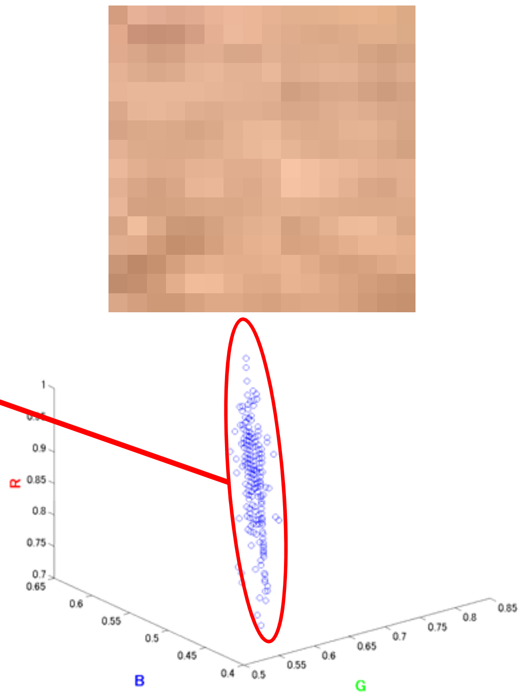
Color-line property

The property that the color-distribution in the local regions of clear image forms straight line[5]

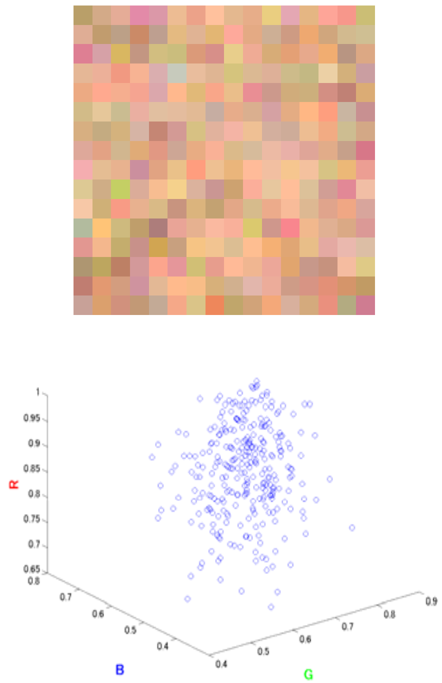
[5] Omer et. al., “Color lines: image specific color representation,” CVPR2004



Straight line

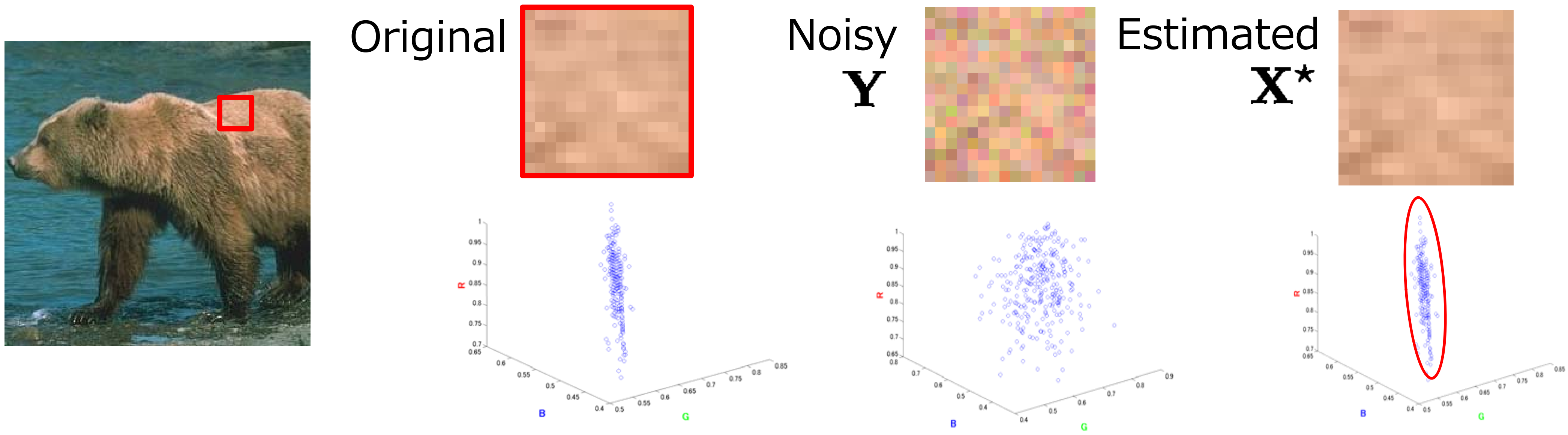


Clear image



Noisy image

Local Color Nuclear Norm (LCNN) [Ono+, CVPR2013, TCI2016]

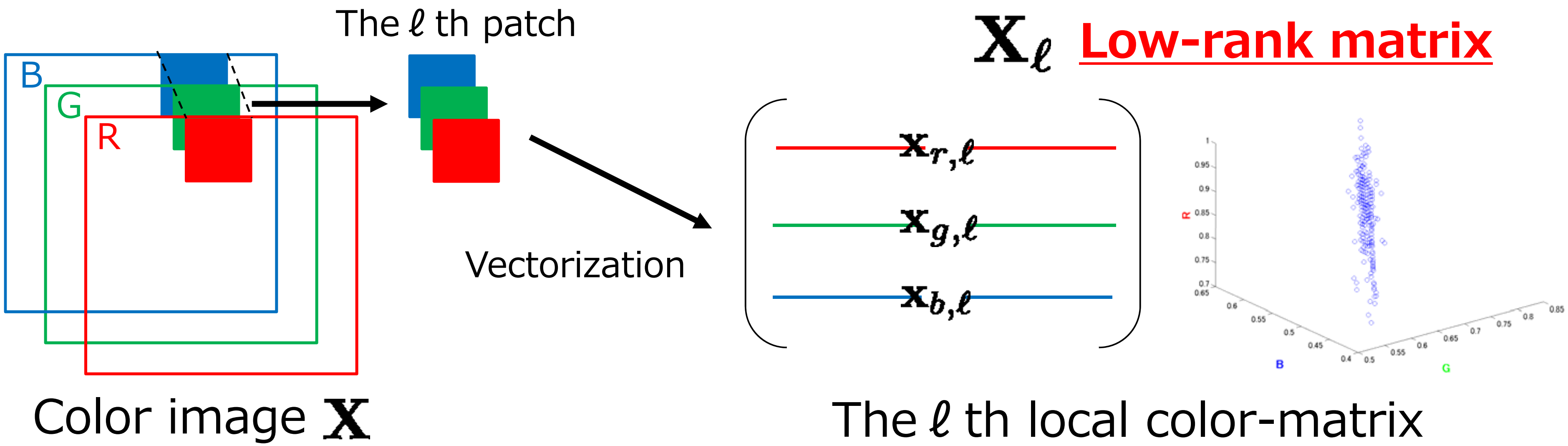


$$\mathbf{X}^\star = \underset{\mathbf{X}\in\mathbb{R}^{3\times N}}{\operatorname{argmin}} \frac{1}{2}\|\mathbf{\Phi}(\mathbf{X}) - \mathbf{Y}\|_F^2 + \boxed{\|\mathbf{X}\|_{\mathrm{LC}}} \cdots (2)$$

Local Color Nuclear Norm

This regularization function promotes the local color-line property

Local Color Nuclear Norm (LCNN) [Ono+, CVPR2013, TCI2016]



- **LCNN :** Sum of all patch's (weighted) nuclear norm

$$\|\mathbf{X}\|_{\mathrm{LC}} = \sum_{\ell=1}^{L} \mu_\ell \|\mathbf{X}_\ell\|_{*,\mathbf{w}} \quad \left(\|\mathbf{X}_\ell\|_{*,\mathbf{w}} = \sum_{i=1}^{3} w_i \sigma_i, \mathbf{w} = [w_1, w_2, w_3] \right)$$

Singular Value Decomposition : $\mathbf{X}_\ell = \mathbf{U}_\ell \mathbf{\Sigma}_\ell \mathbf{V}_\ell^\top, (\mathbf{\Sigma}_\ell = \mathrm{diag}(\sigma_1, \sigma_2, \sigma_3))$

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Problems of LCNN and Purpose of our study

LCNN

Color-distributions are estimated by single low-dimensional linear subspace

Problems:

Color fading degradation arises in the patches not satisfying color-line property

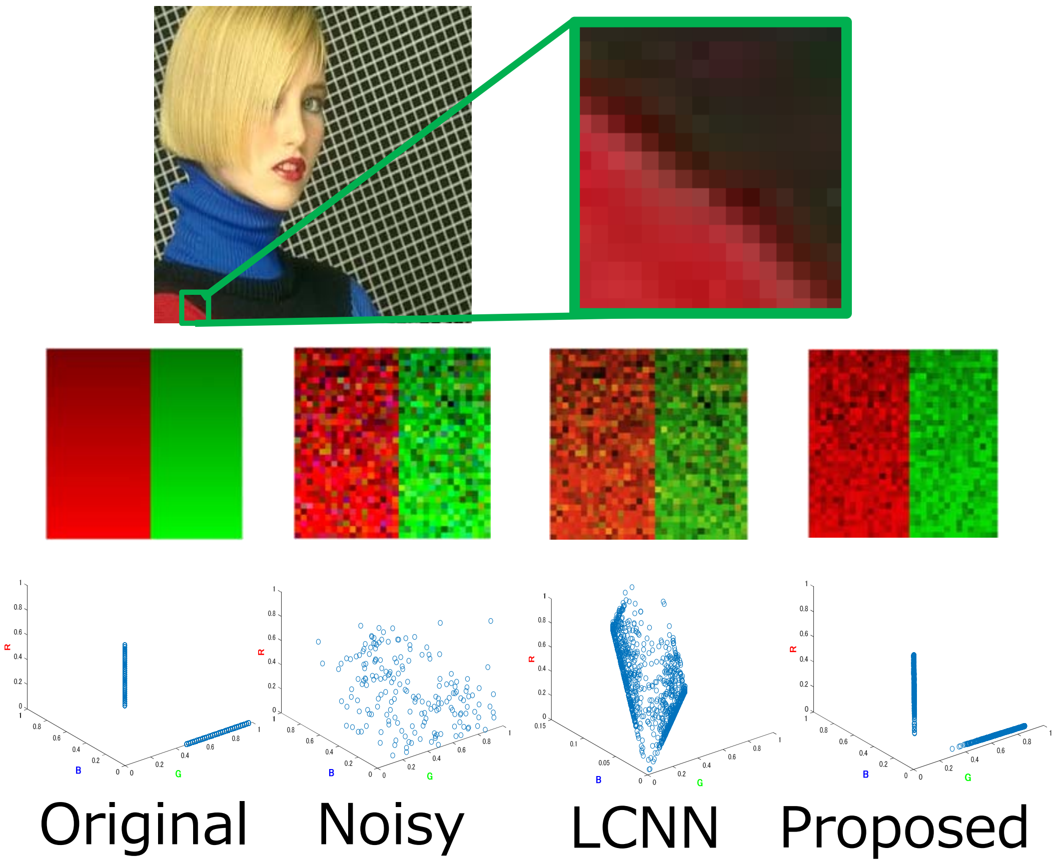
Proposal

Our assumption:

The union of <u>affine subspace</u>※property

(※Straight line/plane which doesn't necessarily intersect with the origin)

Color-distributions are estimated by multiple affine subspaces



Problems of LCNN and Purpose of our study

LCNN

Col

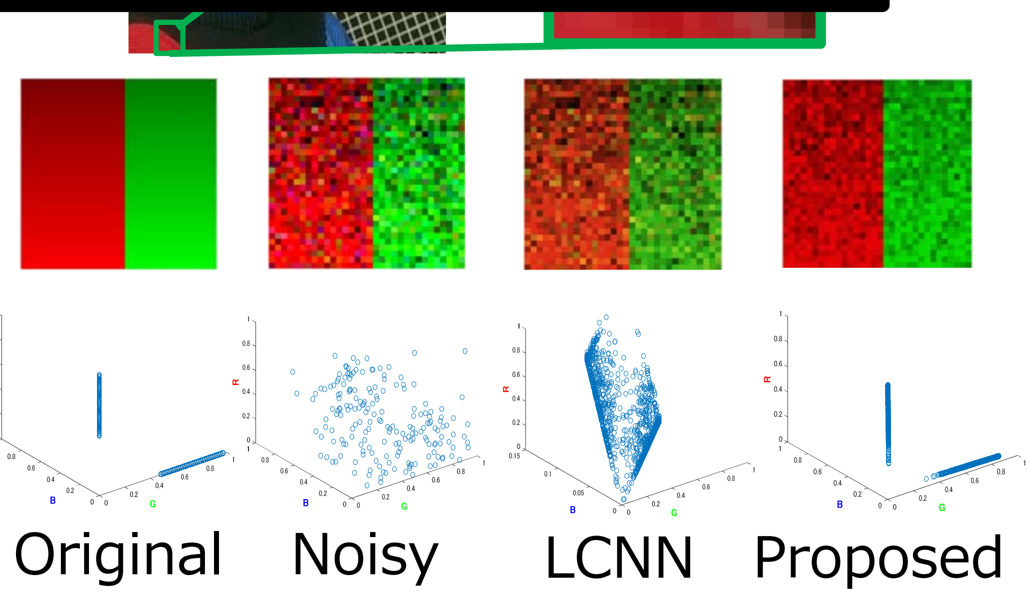
singl

Color fading degradation
arises in the patches
not satisfying color-line property

Purpose of our study
design the regularization function which promotes the union of affine subspace property

Proposal

Our assumption:
The union of affine subspace※property
(※Straight line/plane which doesn't necessarily intersect with the origin)
Color-distributions are estimated by multiple affine subspaces



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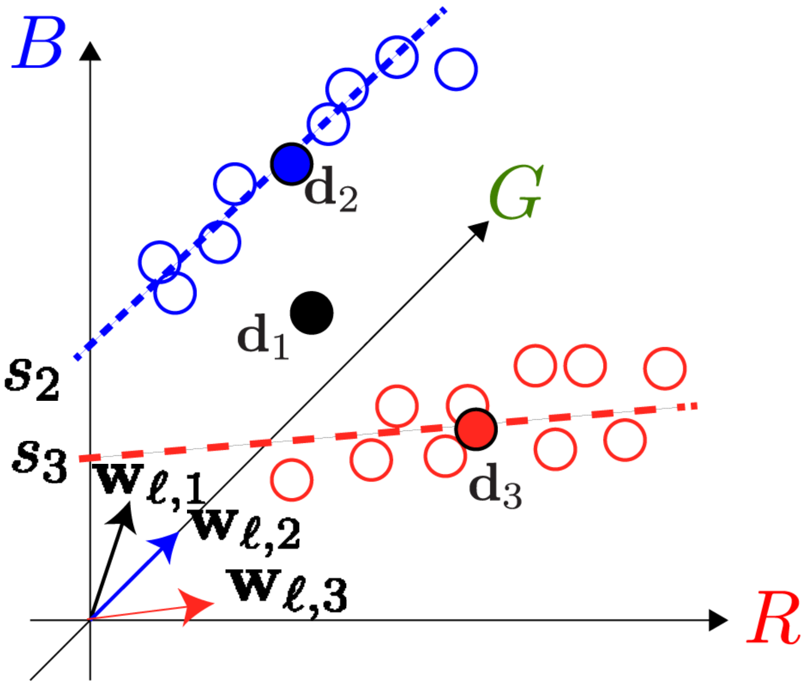
Color artifact removal via Color affine subspace pursuit

Color affine subspace pursuit: identify each affine subspaces

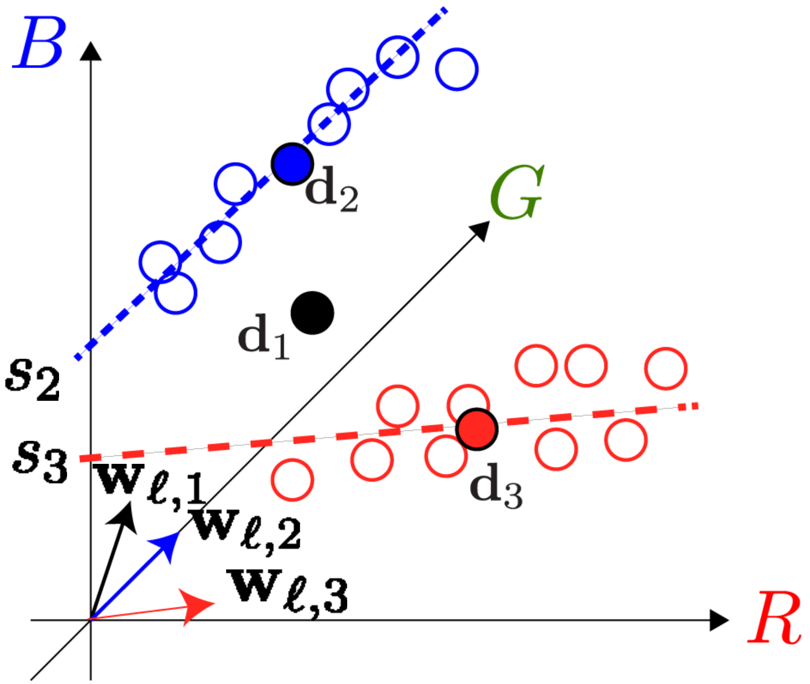


Color-distribution of the ℓth patch

$(\ell = 1, \cdots, L)$

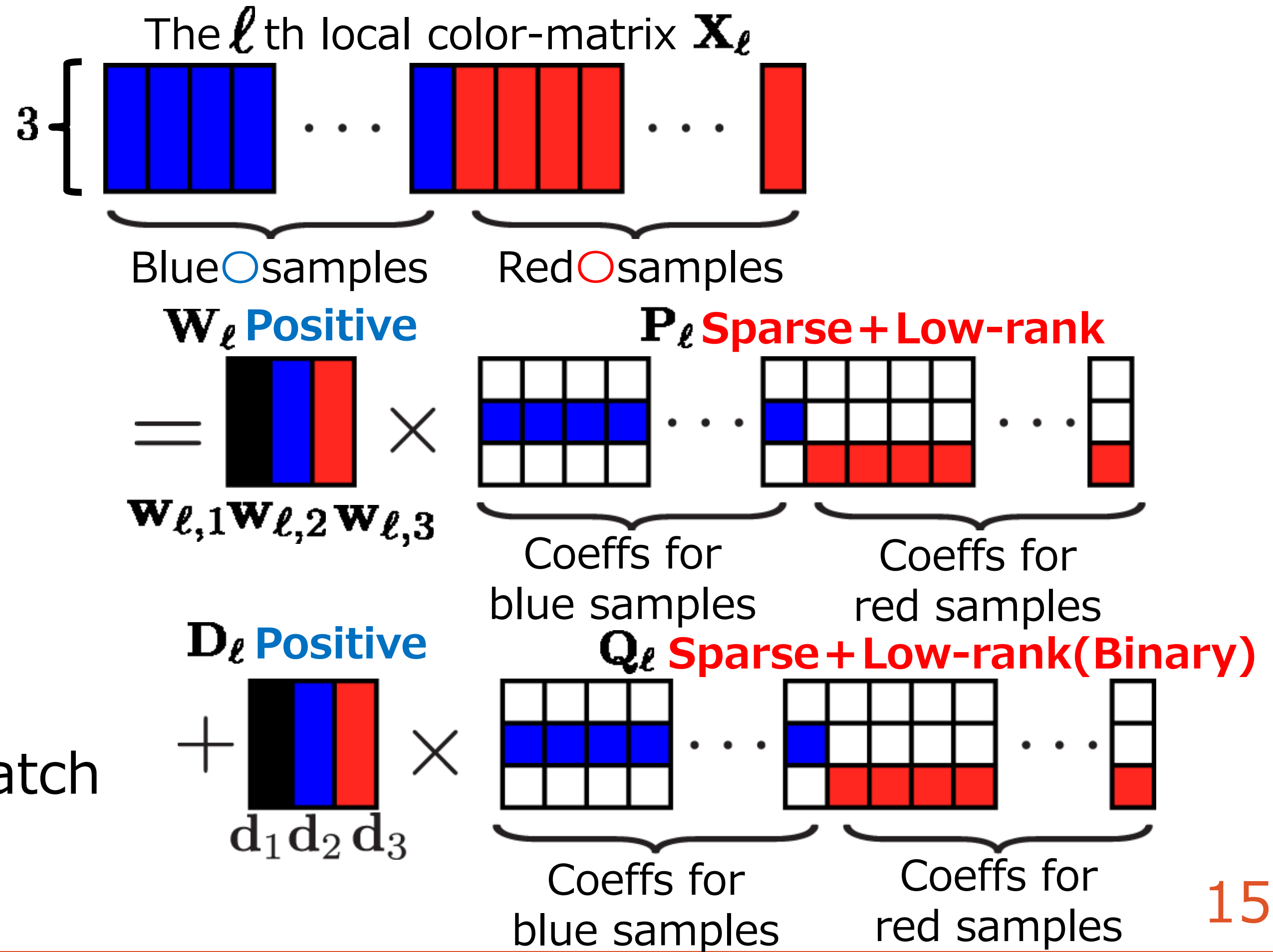
Color artifact removal via Color affine subspace pursuit

Color affine subspace pursuit: identify each affine subspaces



Color-distribution of the ℓth patch

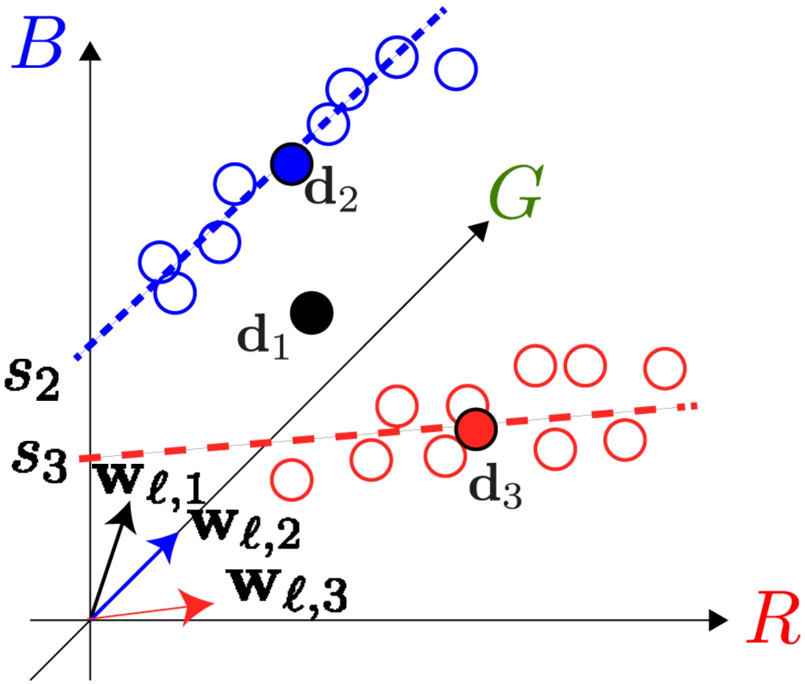
$(\ell = 1, \cdots, L)$



Color artifact removal via Color affine subspace pursuit

$$\mathbf{X}_\ell \approx \mathbf{W}_\ell \mathbf{P}_\ell + \mathbf{D}_\ell \mathbf{Q}_\ell$$

$\mathbf{W}_\ell$: Positive, $\mathbf{P}_\ell$: Sparse + Low-rank, $\mathbf{D}_\ell$: Positive, $\mathbf{Q}_\ell$: Sparse + Low-rank (Binary)



Color-distribution of the ℓth patch

$(\ell = 1, \cdots, L)$

The regularization for promoting the union of affine subspace property

$$\Gamma = (\{\mathbf{W}_\ell\}, \{\mathbf{P}_\ell\}, \{\mathbf{D}_\ell\}, \{\mathbf{Q}_\ell\})$$

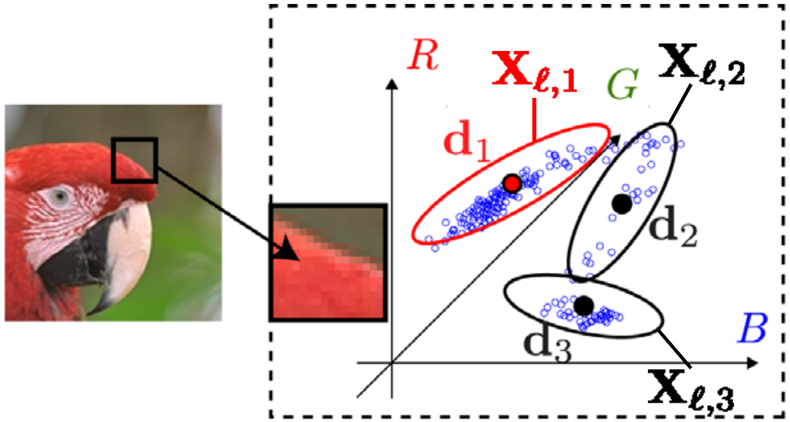
$$\mathcal{R}(\mathbf{X}, \Gamma) = \sum_{\ell=1}^{L} \lambda_1 \|\mathbf{X}_\ell - (\mathbf{W}_\ell \mathbf{P}_\ell + \mathbf{D}_\ell \mathbf{Q}_\ell)\|_F^2 + \lambda_2 \|\mathbf{P}_\ell\|_* + \lambda_3 \|\mathbf{P}_\ell\|_1 + \lambda_4 \|\mathbf{Q}_\ell\|_* + \lambda_5 \|\mathbf{Q}_\ell\|_1 + \iota_{\mathbb{R}_+}(\mathbf{W}_\ell) + \iota_{\mathbb{R}_+}(\mathbf{D}_\ell) + \iota_{\{0,1\}}(\mathbf{Q}_\ell) \quad \cdots (3)$$

$$\mathbf{X}^\star, \Gamma = \operatorname*{argmin}_{\mathbf{X} \in \mathbb{R}^{3 \times N}, \Gamma} \frac{1}{2} \|\mathbf{\Phi}(\mathbf{X}) - \mathbf{Y}\|_F^2 + \mathcal{R}(\mathbf{X}, \Gamma)$$

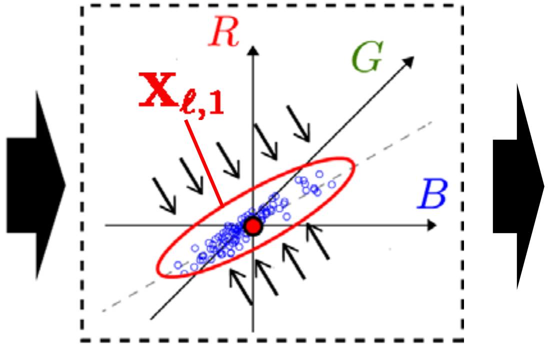
⇒Untractable

cluster-wise LCNN(cLCNN)

Clustering※



Centering※



Weighted NN

$$\|\mathbf{X}_{\ell,1} - \mathbf{D}_{\ell,1}\|_{*,\mathbf{w}}$$

$$\mathbf{X}^* = \underset{\mathbf{X}\in\mathbb{R}^{3\times N}}{\arg\min} \; \frac{1}{2}\|\Phi(\mathbf{X}) - \mathbf{Y}\|_F^2 + \mathcal{R}(\mathbf{X})$$

cLCNN $\|\mathbf{X}\|_{\mathrm{cLC}}^{\mathbf{w}} := \sum_{\ell=1}^{L}\sum_{k=1}^{K} \mu_{\ell,k}\|\mathbf{X}_{\ell,k} - \mathbf{D}_{\ell,k}\|_{*,\mathbf{w}} \quad \cdots (4)$

※Determine center-vectors and cluster assignment by using K-means clustering to pre-restored image

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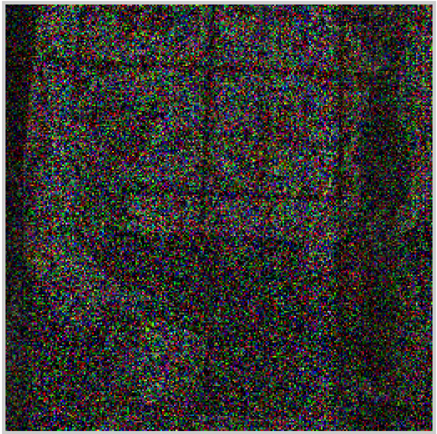
Experiment

Compare VTV [6] , VTV + LCNN and VTV + cLCNN
in compressive sensing reconstruction

$$\mathbf{X}^{\star} = \mathop{\mathrm{argmin}}_{\mathbf{X}\in\mathbb{R}^{3\times N}} \frac{1}{2}\|\boldsymbol{\Phi}(\mathbf{X}) - \mathbf{Y}\|_F^2 + \mathcal{R}(\mathbf{X})$$

Original
(256×256×3)



Observation
(256×256×3)

Missing rate 80%
(Noiselet transform [7] + Sampling)

Test images : BSDS300 [9]
Patch size: $16 \times 16 \times 3$
Overlap : 8 pixels
(Horizontal・Vertical・Diagonal)
Number of Cluster : 3
Optimization algorithm: PDS[8]

[6] X. Bresson 2008.[7]R.Coifman+, 2001.
[8] L. Condat, 2013. [9]D. Martin+, 2001.

Experiment(Numerical comparison)

Image1

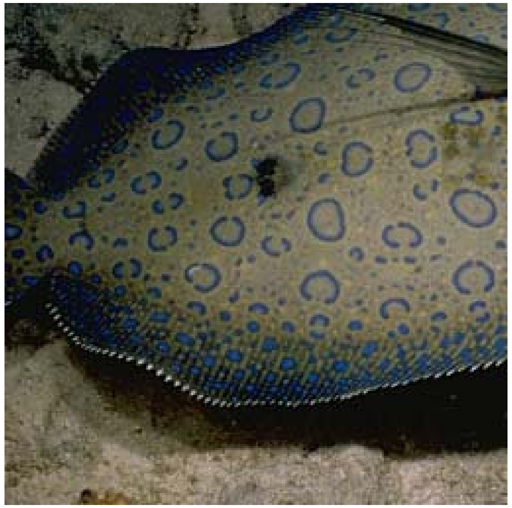


Image2

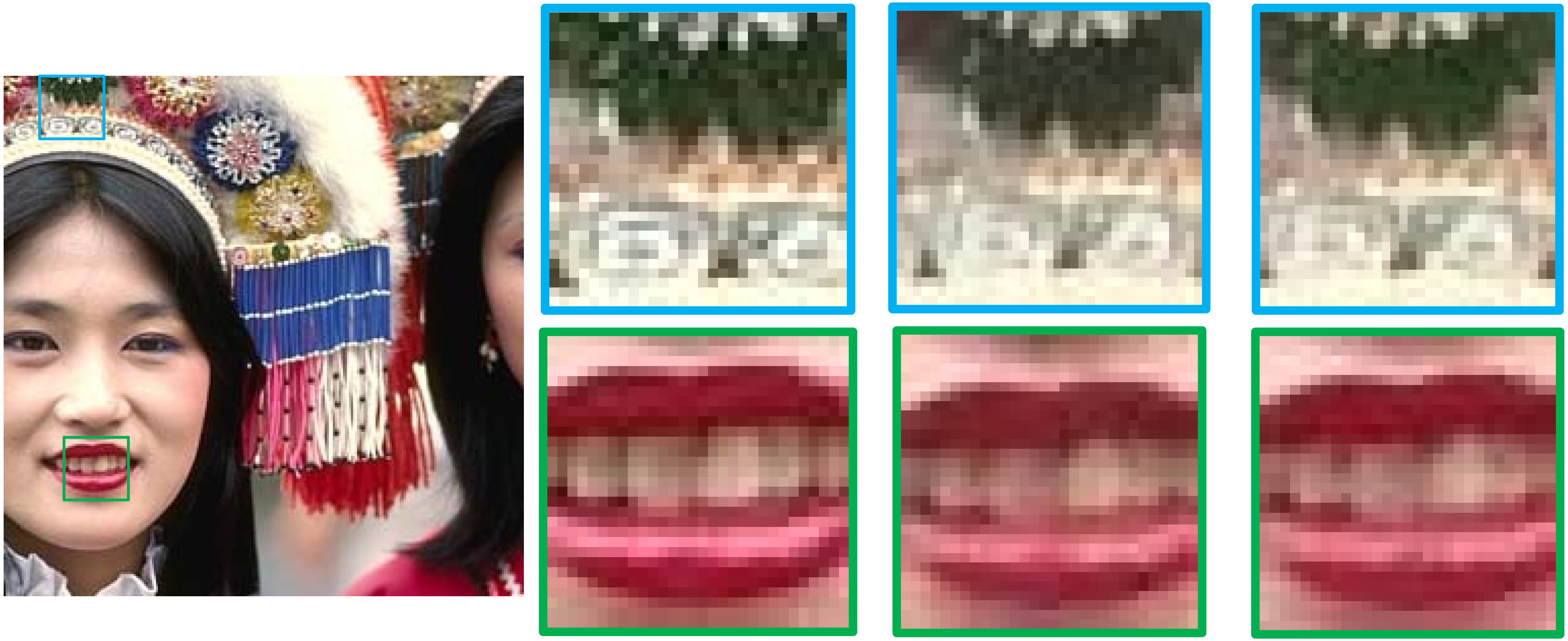
Image3

Image4

Table1:PSNR[dB]

Image	Image1	Image2	Image3	Image4	Ave.
VTV	25.58	27.56	25.65	25.42	28.00
VTV+LCNN	26.37	28.19	26.58	26.58	29.37
VTV+cLCNN	**27.01**	**28.63**	**27.03**	**27.55**	**29.74**

Experiment(Subjective image quality comparison)



Original | **VTV+LCNN** | **VTV+cLCNN**

PSNR[dB]:26.58
dE2000:4.36

PSNR[dB]:**27.55**
dE2000:**3.83**

Experiment(Subjective image quality comparison)

Original **VTV+LCNN** **VTV+cLCNN**

	VTV+LCNN	VTV+cLCNN
PSNR[dB]	26.37	**27.01**
dE2000	5.04	**4.70**

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Conclusion

Proposed method

The color artifact removal method via color affine subspace pursuit
-Apply LCNN after centering each cluster of the local patch.

LCNN Color-distributions are estimated by single low-dimensional liner subspace

Restoration accuracy for each patch which forms a union of affine subspace is not good

Result

・Proposed methods is superior to LCNN in the color-distribution approximate
・Both restoration error and subjective image quality were improved

Convex optimization Algorithm

Primal-Dual Splitting Algorithm (PDS) [8]

$$\mathbf{x}^\star = \arg\min_{\mathbf{x}\in\mathbb{R}^N} g(\mathbf{x}) + h(\mathbf{L}\mathbf{x})$$

$\mathbb{R}^N$:Real N-space

Optimum solution $\mathbf{x}^\star$ is provided by bellow

$$\left\lfloor \begin{array}{l} \mathbf{x}_{k+1} := \mathrm{prox}_{\gamma_1 g}[\mathbf{x}_k - \gamma_1 \mathbf{L}^* \xi_k] \\ \xi_{k+1} := \mathrm{prox}_{\gamma_2 h^*}[\xi_k + \gamma_2 \mathbf{L}(2\mathbf{x}_{k+1} - \mathbf{x}_k)]. \end{array} \right.$$

[8] L. Condat, "A primaldual splitting method for convex optimization involving lipschitzian, proximable and linear composite terms," in *J. Optimization Theory and Applications*, 2013.

Pre-restored image by vectorial TV

$$\mathbf{c}_{\mathrm{pre}} = \underset{\mathbf{c}\in\mathbb{R}^{3N}}{\arg\min} \|\mathbf{D}\mathbf{c}\|_{1,2} \ \ s.t. \begin{cases} \|\boldsymbol{\Phi}\mathbf{c}-\mathbf{y}\| \leq \epsilon \\ \mathbf{c} \in [0,1]^{3N} \end{cases}$$

$\mathbf{c}$:Desired image
$\mathbf{y}$:Degraded image
$\mathbf{c}_{\mathrm{pre}}$:Restored image
ϵ :Error margin
$\boldsymbol{\Phi}$:The matrix which express the process of degradation
$\mathbf{D}$:The discrete gradient operator

$$\mathbf{D} : \mathbb{R}^{3N} \to \mathbb{R}^{6N} : \mathbf{c} \to (\mathbf{d}_v^{\top} \mathbf{d}_h^{\top})^{\top}$$

$\mathbf{d}_v$:Vertical difference of a color image.
$\mathbf{d}_h$:Horizontal differences of a color image

[9] X. Bresson and T. F. Chan,"Fast dual minimization of the vectorial total variation norm and applications to color image processing, " *Inverse Probl.Imag.*, vol. 2, no. 4, pp. 455–484, 2008.

Detail of our experiment

$$\mathbf{X}^{\star} = \underset{\mathbf{X}\in\mathbb{R}^{3\times N}}{\operatorname{argmin}} \ \frac{1}{2}\|\mathbf{\Phi}(\mathbf{X}) - \mathbf{Y}\|_F^2 \ + \ \lambda\mathcal{R}(\mathbf{X})$$

$\mathcal{R}(\mathbf{X})$	$\|\cdot\|_{\mathrm{VTV}}$	$\|\cdot\|_{\mathrm{VTV}} + \|\cdot\|_{\mathrm{LCNN}}$	$\|\cdot\|_{\mathrm{VTV}} + \|\cdot\|_{\mathrm{cLCNN}}$
Run time(sec)	7.27	21.19	93.53
Image size	256×256×3	256×256×3	256×256×3
Patch size	-	16×16×3	16×16×3
Overlap	-	8pixels	8pixels
$[w_1, w_2, w_3]$	-	[0.001 1 1]	[0.001 1 1]
λ	1	VTV(1),LCNN(2)	VTV(1),cLCNN(2)