3D Color CLUT Compression by Multi-Scale Anisotropic Diffusion

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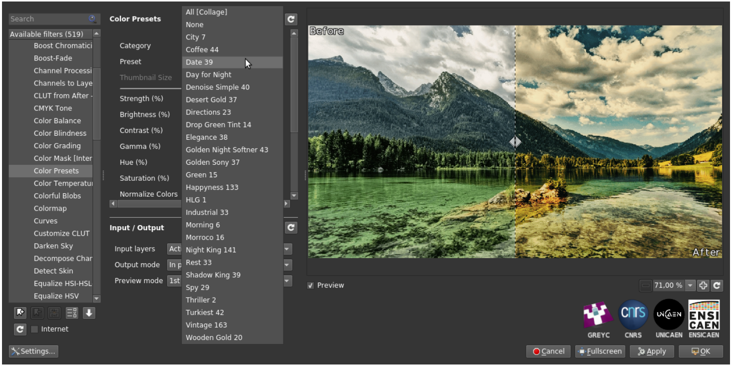
Context

GREYC's Magic for Image Computing

A Full-Featured Open-Source Framework for Image Processing

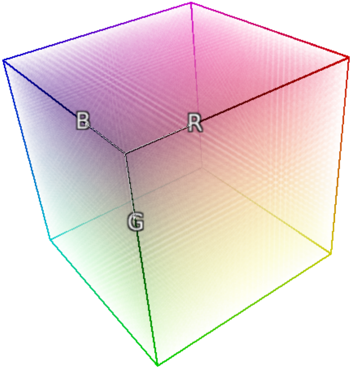
GREYC's **M**agic for **I**mage **C**omputing

https://gmic.eu



- **Application context:**
  Provide *various colorimetric transformations* available in our open-source framework for image processing.

What is a *CLUT* (*Color Look-Up Table*) ?



(a) *CLUT* **F** : *RGB* $\rightarrow$ *RGB*, visualized in $3D$

(b) Original color image

(c) Image after transformation **F**

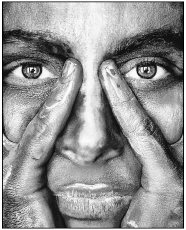
Examples of of *CLUT*-based transformations

Original image

“60’s”

“Color Negative”

“Orange Tone”



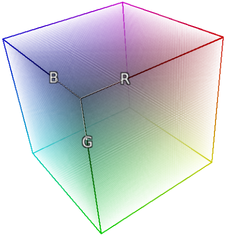
“Ilford Delta 3200”

“Backlight Filter”

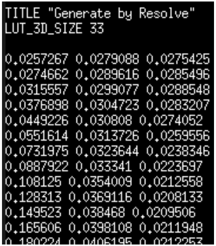
“Bleach Bypass”

“Late Sunset”

Standard ways of storing a *CLUT*



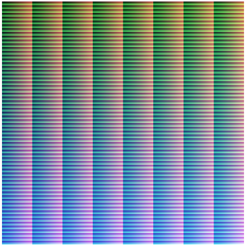
a) a *CLUT* is a $3D$ dense color volume



TITLE "Generate by Resolve"
LUT_3D_SIZE 33

0.0257267 0.0279088 0.0275425
0.0274662 0.0289616 0.0285496
0.0315557 0.0299077 0.0288548
0.0376898 0.0304723 0.0283207
0.0449226 0.030808 0.0274052
0.0551614 0.0313726 0.0259556
0.0731975 0.0323644 0.0238346
0.0887922 0.033341 0.0223697
0.108125 0.0354009 0.0212558
0.128313 0.0369116 0.0208133
0.149523 0.038468 0.0209506
0.165606 0.0398108 0.0211948

b) Storage as a `.cube`



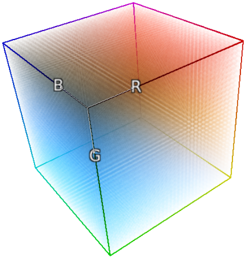
c) Storage as a `.png`

In both cases, lossless compression, but restricted to small sizes:

1. `.cube` file: *ASCII* zipped format (*CLUT* $64^3 \approx$ 1 Mo)
2. `.png` file: $2D$ image (*CLUT* $64^3 \approx$ 64 to 100 Ko)

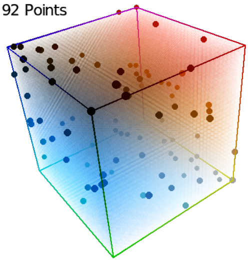
$\Rightarrow$ **Issue:** Promote a large-scale distribution of *CLUT*s (**500+**), by limiting the number of parameters as much as possible.

Compression: Let **F** : *RGB* → *RGB* be a 3*D CLUT*.
We generate $\mathcal{K}$, a smaller representation based on the storage of a set of color keypoints.



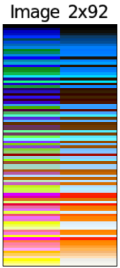
Original CLUT **F**

→



Determination of 3*D* color keypoints $\mathcal{K}$

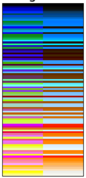
→



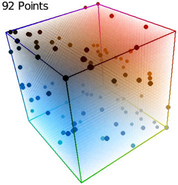
Storage in compressed form

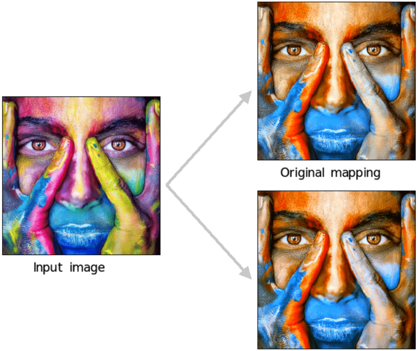
Our approach: CLUT decompression

Decompression: A $3D$ interpolation based on anisotropic diffusion *PDEs* is applied to $\mathcal{K}$ in order to generate a reconstructed CLUT $\widetilde{\mathbf{F}}$ visually close to $\mathbf{F}$.



→





Stockage in compressed form

Decompressed CLUT $\widetilde{\mathbf{F}}$

No visible perceptual differences between the two transformations

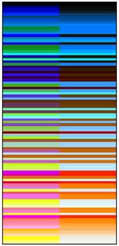
Reconstruction principles (1/3)

Let $\mathbf{F} : RGB \rightarrow RGB$ be a $3D$ *CLUT*.
It is assumed that its sparse representation is known.

$$\mathcal{K} = \{\mathbf{K}_k \in RGB \times RGB \mid k = 1 \dots N\}$$

i.e the color keypoints N, located in the *RGB* cube.

Image 2x92



The k^{th} keypoint of $\mathcal{K}$ is defined by vecteur

$$\mathbf{K}_k = (\mathbf{X}_k, \mathbf{C}_k) = (x_k, y_k, z_k, R_k, G_k, B_k),$$

where $\mathbf{X}_k = (x_k, y_k, z_k)$ is the $3D$ keypoint position in the *RGB* cube, and $\mathbf{C}_k = (R_k, G_k, B_k)$ its associated color.

Reconstruction principles (2/3)

We propagate/average the colors $\mathbf{C}_k$ of the keypoints in the whole *RGB* domain throgh an **anisotropic diffusion** process

- Let $d_{\mathcal{K}} : RGB \rightarrow \mathbb{R}^+$, the distance function to the set of keypoints $\mathcal{K}$:

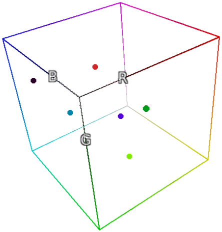
$$\forall \mathbf{X} \in RGB, \qquad d_{\mathcal{K}(\mathbf{X})} = \inf_{k \in 0 \ldots N} \|\mathbf{X} - \mathbf{X}_k\|$$

- *CLUT* $\mathbf{F}$ is reconstructed by solving the following anisotropic diffusion *PDE* :

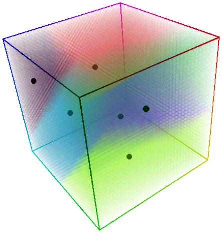
$$\forall \mathbf{X} \in RGB, \qquad \frac{\partial \mathbf{F}}{\partial t}(\mathbf{X}) = m_{(\mathbf{X})} \, \frac{\partial^2 \mathbf{F}}{\partial \eta^2}(\mathbf{X})$$

where $\eta = \dfrac{\nabla d_{\mathcal{K}(\mathbf{X})}}{\|\nabla d_{\mathcal{K}(\mathbf{X})}\|}$ and $m_{(\mathbf{X})} = \begin{cases} 0 & \text{if} \quad \exists k, \quad \mathbf{X} = \mathbf{X}_k \\ 1 & \text{otherwise} \end{cases}$

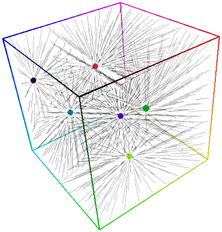
Reconstruction principles (3/3)



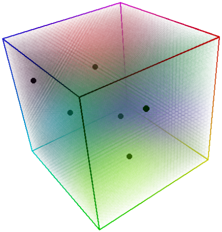
(a) Set $\mathcal{K}$ of known keypoints



(b) Initial state $\mathbf{F}_{t=0}$ (*Voronoï 3D smoothed*)



(c) Diffusion orientations η



(d) State at convergence (*PDE* Solution)

Spatial discretization (1/2)

$d_{\mathcal{K}}$ is not derivable on its local maxima.
We propose the following numerical scheme for discretization:

$$\nabla d_{\mathcal{K}(\mathbf{x})} = \left(\begin{array}{c} \mathrm{maxabs}(\partial_x^{\mathrm{for}} d_{\mathcal{K}}, \partial_x^{\mathrm{back}} d_{\mathcal{K}}) \\ \mathrm{maxabs}(\partial_y^{\mathrm{for}} d_{\mathcal{K}}, \partial_y^{\mathrm{back}} d_{\mathcal{K}}) \\ \mathrm{maxabs}(\partial_z^{\mathrm{for}} d_{\mathcal{K}}, \partial_z^{\mathrm{back}} d_{\mathcal{K}}) \end{array} \right)$$

where

$$\mathrm{maxabs}(a,b) = \begin{cases} a & \text{if } |a| > |b| \\ b & \text{otherwise} \end{cases}$$

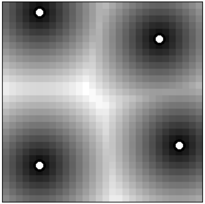
and

$$\partial_x^{\mathrm{for}} d_{\mathcal{K}} = d_{\mathcal{K}(x+1,y,z)} - d_{\mathcal{K}(x,y,z)}$$

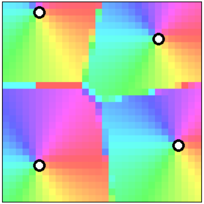
$$\partial_x^{\mathrm{back}} d_{\mathcal{K}} = d_{\mathcal{K}(x,y,z)} - d_{\mathcal{K}(x-1,y,z)}$$

(Discrete *forward*/*backward* first derivative approximations).

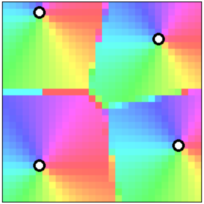
Spatial discretization (2/2)



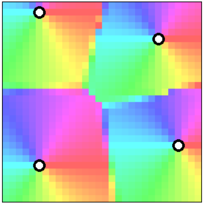
(a) Keypoints and distance function $d_{\mathcal{K}}$



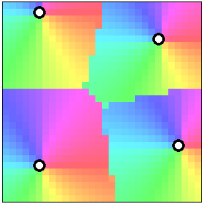
(b) Estimation of η using *forward* scheme $\partial^{\text{for}} d_{\mathcal{K}}$



(c) Estimation of η using *backward* scheme $\partial^{\text{back}} d_{\mathcal{K}}$



(d) Estimation of η using *centred* scheme $\frac{1}{2}(\partial^{\text{for}} d_{\mathcal{K}} + \partial^{\text{back}} d_{\mathcal{K}})$



(e) Estimation of η using proposed scheme

Temporal discretization

For the sake of algorithmic efficiency, we discrete the *PDE* by a *semi-implicit* scheme:

$$\frac{\mathbf{F}^{t+dt} - \mathbf{F}^{t}}{dt} = m_{(\mathbf{X})} \left[\mathbf{F}^{t}_{(\mathbf{X}+\eta)} + \mathbf{F}^{t}_{(\mathbf{X}-\eta)} - 2\,\mathbf{F}^{t+dt}_{(\mathbf{X})} \right]$$

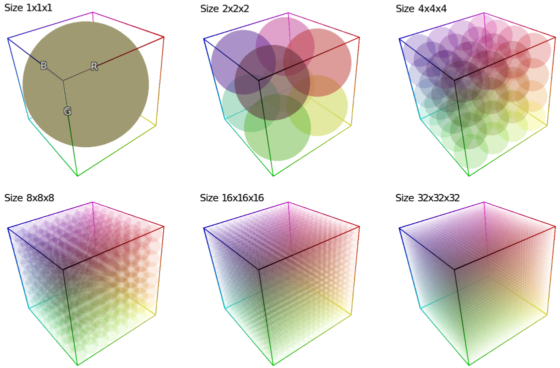
By choosing dt appropriately, we simplify the scheme by:

$$\begin{cases} \mathbf{F}^{t+dt}_{(\mathbf{X})} = \mathbf{F}^{t}_{(\mathbf{X})} & \text{if } m_{(\mathbf{X})} = 0 \\ \mathbf{F}^{t+dt}_{(\mathbf{X})} = \frac{1}{2} \left[\mathbf{F}^{t}_{(\mathbf{X}+\eta)} + \mathbf{F}^{t}_{(\mathbf{X}-\eta)} \right] & \text{otherwise} \end{cases}$$

where $\mathbf{F}^{t}_{(\mathbf{X}+\eta)}$ and $\mathbf{F}^{t}_{(\mathbf{X}-\eta)}$ are accurately estimated using tricubic spatial interpolation.

Multi-scale resolution

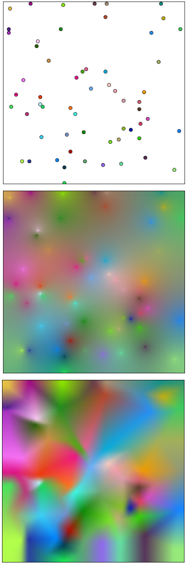
- Speed-up of convergence through **multi-scale resolution**.

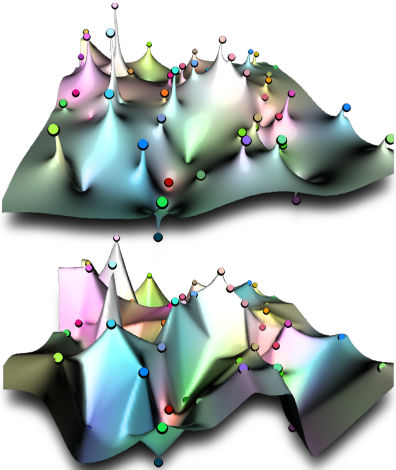


→ Reduction of the number of required iterations per scale (≈ 20).
→ Total algorithmic complexity for a size r^3 : $O(log_2(r)\ r^3)$.
→ Reconstruction of a 64^3 *CLUT* in less than 1s.

Isotropic/Anisotropic comparison

(a)
(b)
(c)

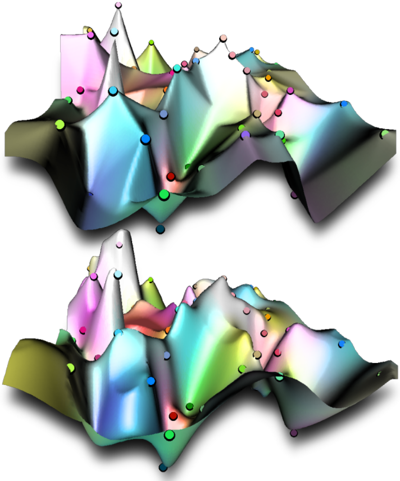




(a) Color Keypoints $\mathcal{K}$
(b) **Isotropic** reconstruction, in $O(log_2(r)\ r^3)$
(c) **Anisotropic** reconstruction, in $O(log_2(r)\ r^3)$

Comparison with *RBFs* (Radial Basis Functions)

(a)
(b)
(c)

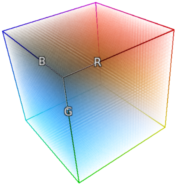


(a) Color Keypoints $\mathcal{K}$
(b) **Anisotropic** reconstruction, in $O(log_2(r)\ r^3)$
(c) **RBFs** reconstruction, in $O(N^3 + N\ r^3)$.

Compression: Generation of keypoints

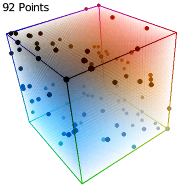
Let $\mathbf{F}$ be the *CLUT* to be compressed. The compression:

- Generates a set $\mathcal{K}$ of N keypoints representing $\mathbf{F}$.
- $\widetilde{\mathbf{F}}_N$ the reconstructed *CLUT* from $\mathcal{K}$ must be close enough to $\mathbf{F}$.
  Two quality criteria for reconstruction:
  - $\Delta_{\text{max}} = 8$, maximum reconstruction error allowed,
  - $\Delta_{\text{moy}} = 2$, average reconstruction error for the entire *CLUT*



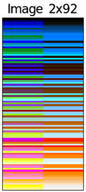
Original *CLUT* $\mathbf{F}$

$\longrightarrow$



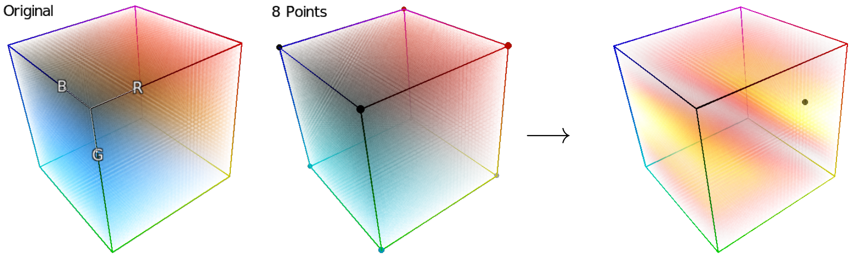
Determination of 3*D* color keypoints $\mathcal{K}$

$\longrightarrow$



Storage in compressed form

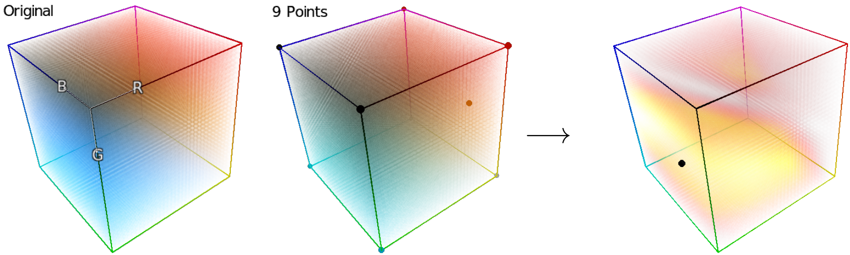
1. Initialization of $\mathcal{K} = \{(\mathbf{X}_k, \mathbf{F}_{(\mathbf{X}_k)} \mid k = 1 \ldots 8\}$ (the 8 vertices of the cube).



$\Rightarrow$ Calculation of the L_2 reconstruction error: $E_{N(\mathbf{x})} = \|\mathbf{F}_{(\mathbf{x})} - \widetilde{\mathbf{F}}_{N(\mathbf{x})}\|$.

Compression: Generation of keypoints

2. Iterative addition into $\mathcal{K}$ of the keypoints with maximum reconstruction error, while $E_{max} < \Delta_{max}$ or $E_{moy} < \Delta_{moy}$.



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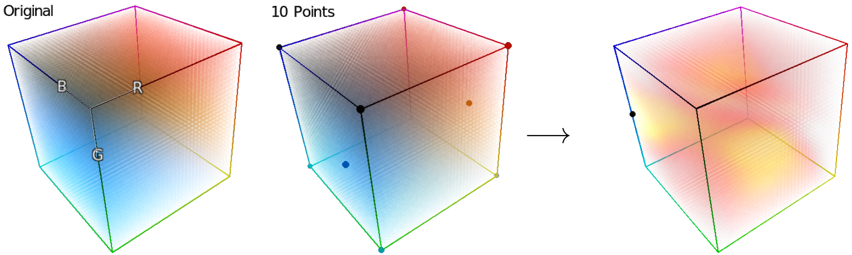

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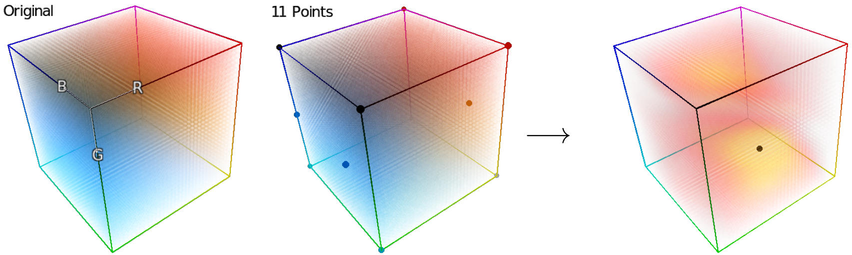

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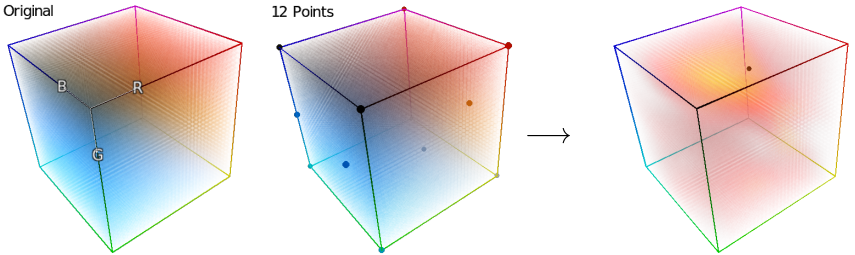

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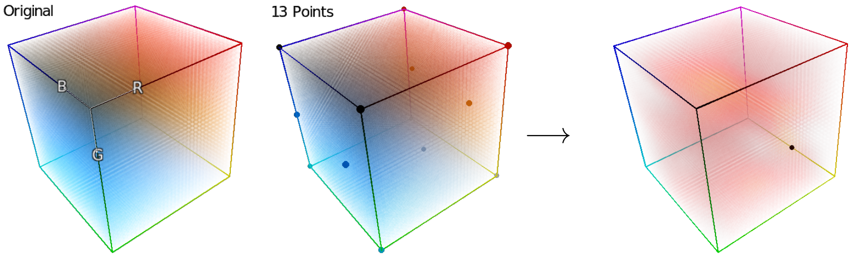

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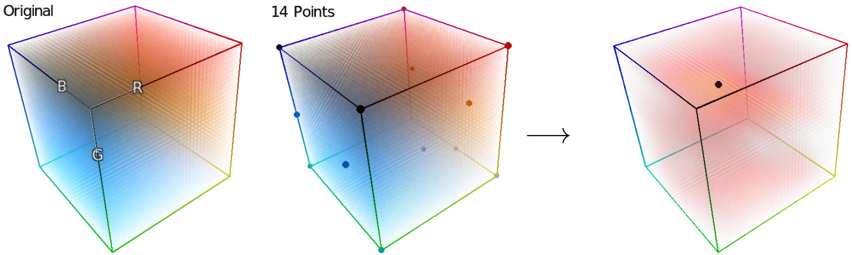

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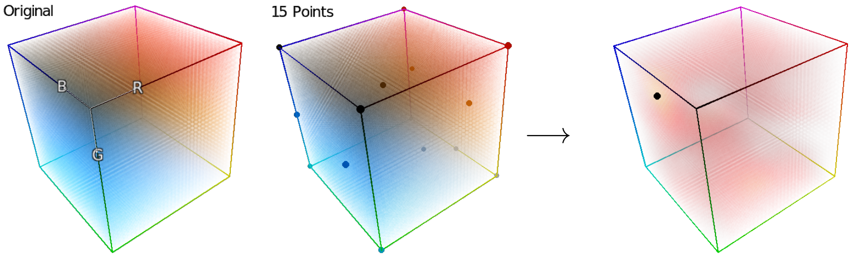
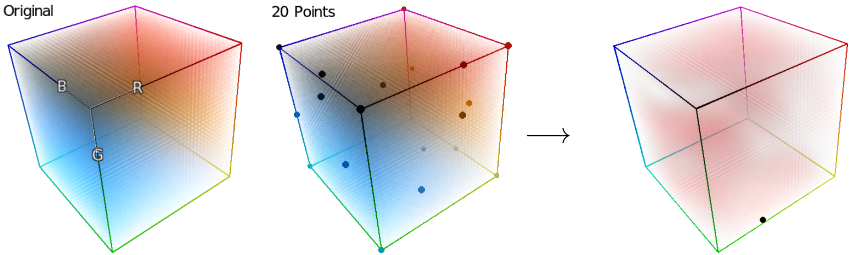


$\Rightarrow$ Calculation of the reconstruction error: $E_{N(\mathbf{x})} = \|\mathbf{F}_{(\mathbf{x})} - \widetilde{\mathbf{F}}_{N(\mathbf{x})}\|$.

2. Iterative addition into $\mathcal{K}$ of the keypoints with maximum reconstruction error, while $E_{\max} < \Delta_{\max}$ or $E_{moy} < \Delta_{moy}$.



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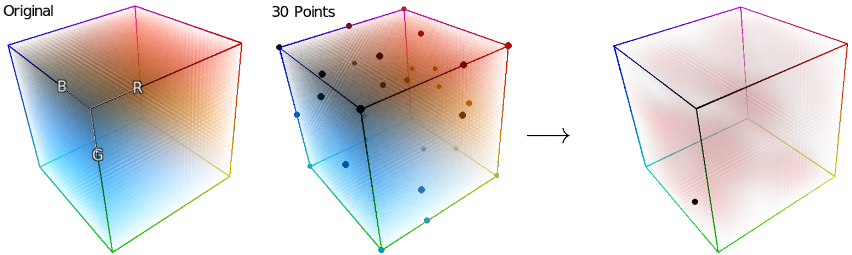

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Compression: Generation of keypoints

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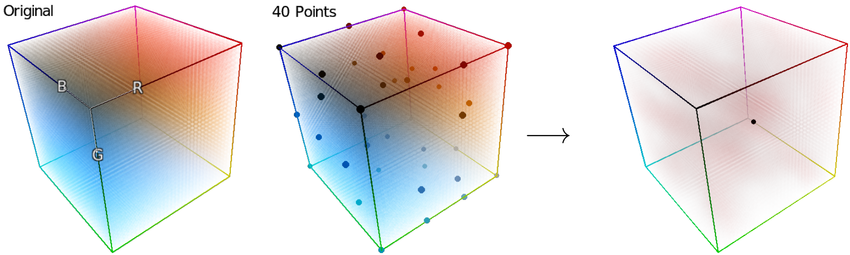
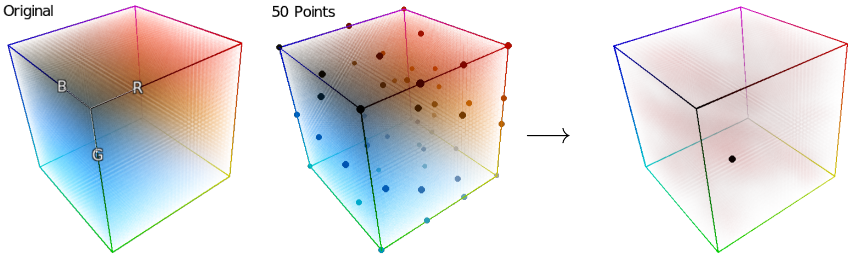


$\Rightarrow$ Calculation of the reconstruction error: $E_{N(\mathbf{x})} = \|\mathbf{F}_{(\mathbf{x})} - \widetilde{\mathbf{F}}_{N(\mathbf{x})}\|$.

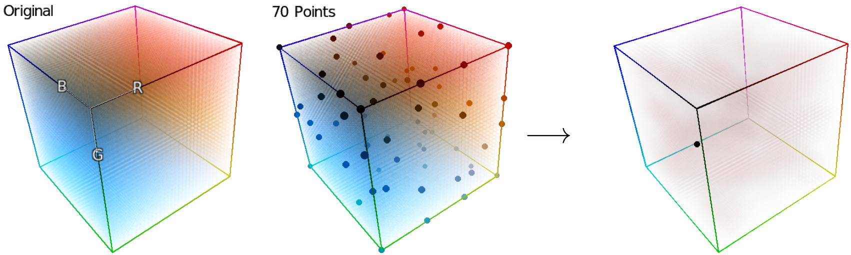
2. Iterative addition into $\mathcal{K}$ of the keypoints with maximum reconstruction error, while $E_{max} < \Delta_{max}$ or $E_{moy} < \Delta_{moy}$.



$\Rightarrow$ Calculation of the reconstruction error: $E_{N(\mathbf{x})} = \|\mathbf{F}_{(\mathbf{x})} - \widetilde{\mathbf{F}}_{N(\mathbf{x})}\|$.

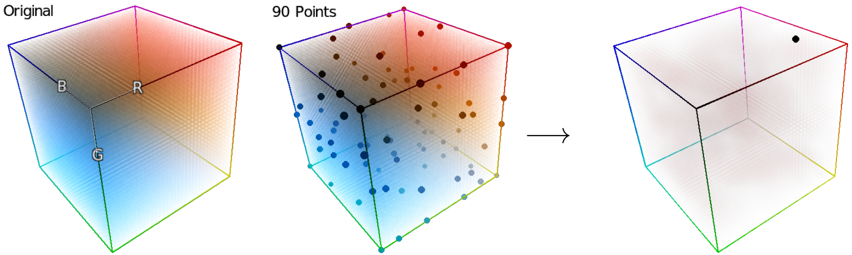
Compression: Generation of keypoints

2. Iterative addition into $\mathcal{K}$ of the keypoints with maximum reconstruction error, while $E_{\text{max}} < \Delta_{\text{max}}$ or $E_{\text{moy}} < \Delta_{\text{moy}}$.



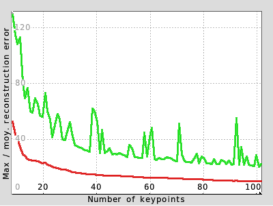
$\Rightarrow$ Calculation of the reconstruction error: $E_{N(\mathbf{x})} = \|\mathbf{F}_{(\mathbf{x})} - \widetilde{\mathbf{F}}_{N(\mathbf{x})}\|$.

2. Iterative addition into $\mathcal{K}$ of the keypoints with maximum reconstruction error, while $E_{\text{max}} < \Delta_{\text{max}}$ or $E_{\text{moy}} < \Delta_{\text{moy}}$.

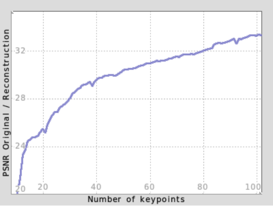


$\Rightarrow$ Calculation of the reconstruction error: $E_{N(\mathbf{x})} = \|\mathbf{F}_{(\mathbf{x})} - \widetilde{\mathbf{F}}_{N(\mathbf{x})}\|$.

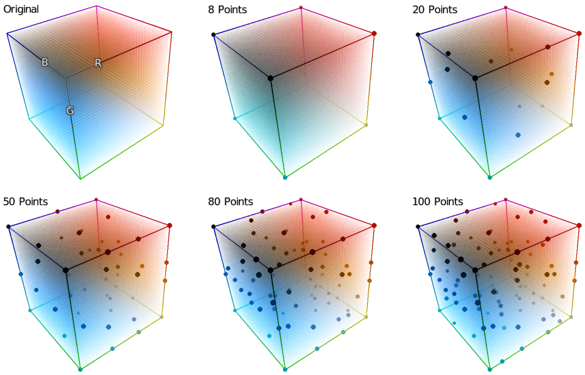
Adding keypoints for *CLUT* compression



(a) max/average error



(b) PSNR evolution



(c) Iterative addition of keypoints

CLUT Compression results

- Individual measurements:

CLUT name	`Bourbon 64`	`Faded 47`	`Milo 5`	`Cubicle 99`
Resolution	16^3	32^3	48^3	64^3
Size in `.cube.zip`	23.5 Kb	573 Kb	3 Mb	1.2 Mb
Size in `.png`	**3.7 Kb**	**22 Kb**	**72 Kb**	**92 Kb**
Number of Keypoints	562	294	894	394
PSNR	45.8 dB	45.6 dB	45 dB	45.2 dB
Compression time	28 s	92 s	1180 s	561 s
Decompression time	67 ms	157 ms	260 ms	437 ms
Keypoints in `.png`	**1.9 Kb**	**1.5 Kb**	**4.2 Kb**	**1.9 Kb**
%cRate / `.cube.zip`	92.1%	99.7%	99.8%	99.8%
%cRate / `.png`	49.5%	93.3%	94.2%	98%

- General measurement: A set of 552 *CLUT*s (**708 Mo**), mix of `.cube.zip` and `.png`, compressed in **2.5 Mo.**

$\Rightarrow$ Overall compression rate of 99.65%

Conclusions/Future prospects

- The *CLUT* compression/decompression techniques are surprisingly effective. Adequacy of the proposed 3*D* anisotropic diffusion model to the type of data processed (smooth, volumetric, color-valued).
- Algorithms integrated into *G'MIC*, our full-featured open-source framework for image processing

G'MIC
GREYC's Magic for Image Computing
A Full-Featured Open-Source Framework for Image Processing

https://gmic.eu

⇒ **Reproductible** research , **open-source** and **reviewable** implementation.

⇒ Already massive **general public** use (thousands of users).

- **Future prospects:** Integration into any type of image and video processing software is recommended.

Thank you for your attention!

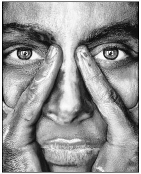
Any questions?

Original image

“60’s”

“Color Negative”

“Orange Tone”



“Ilford Delta 3200”

“Backlight Filter”

“Bleach Bypass”

“Late Sunset”