Jacobi Retinex Algorithm and various sampling methods

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Introduction

The Retinex algorithm is a computational method for image enhancement that separates an image into illumination and reflectance components, suppressing the effects of illumination—an approach inspired by the human visual system [1]. Our Jacobi Retinex algorithm [3] processes the image across multiple resolutions, from coarse to fine. At each level of the resolution pyramid, the image is convolved with a Laplacian filter, then Jacobi iteration is employed to reintegrate the image partially.

Our method reframes the McCann99 Retinex [2] in a center-surround framework that unifies three major classes of Retinex algorithms: center-surround processing, lightness computation, and path-based methods.

One of the key components of the Jacobi Retinex framework is the sampling method used to construct the resolution pyramid. In this work, we compare six different sampling kernels—Lanczos-2, Lanczos-3, Gaussian, Sinc, bicubic, and osculatory rational interpolation—in terms of how well they preserve information from the original image.

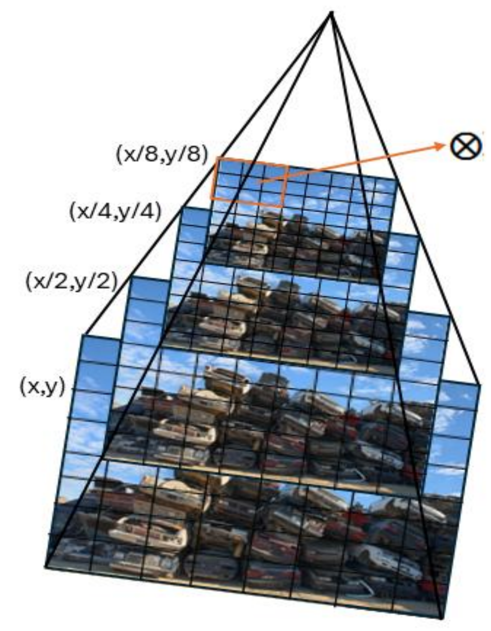
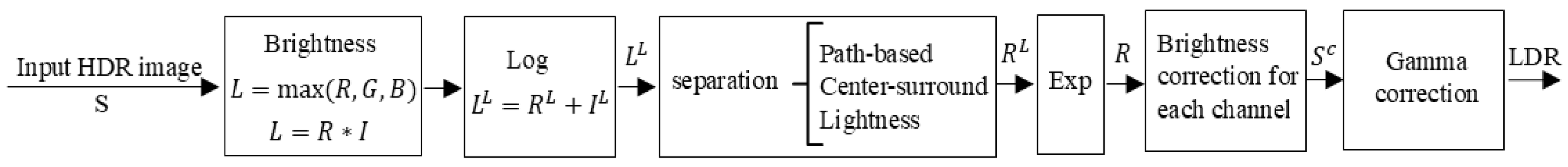
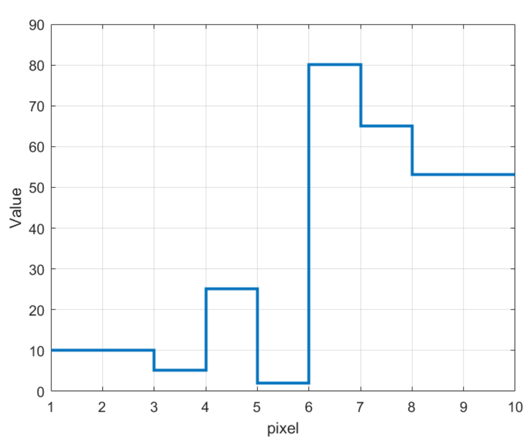
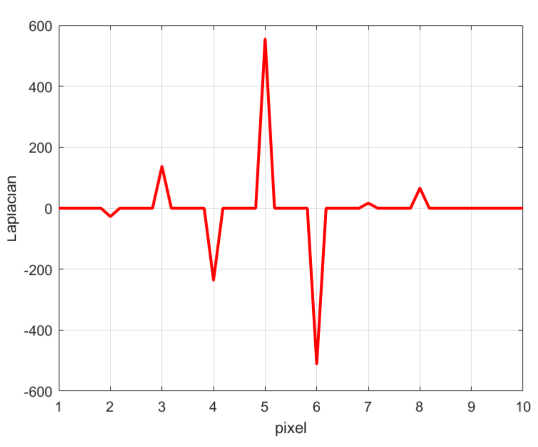


Image sampling pyramid

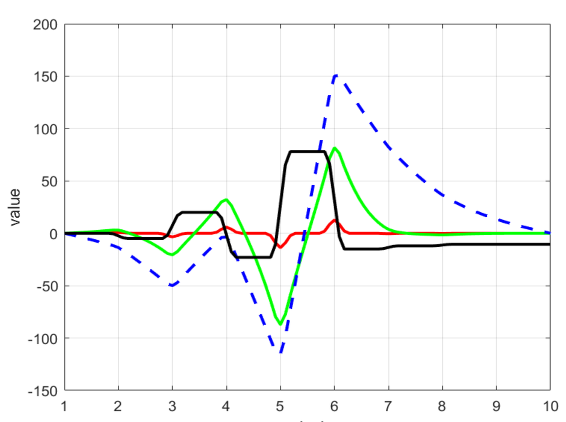




Image



Laplacian of image



Iterative incomplete integration

Aim and Objectives

The main goal of this project is to identify the sampling method that best preserves the information content of the original image within our Retinex framework. By selecting an optimal sampling approach in our Retinex algorithm, we aim to achieve faster convergence, improved image quality, and better preservation of key image properties such as lightness ordering.

Methodology

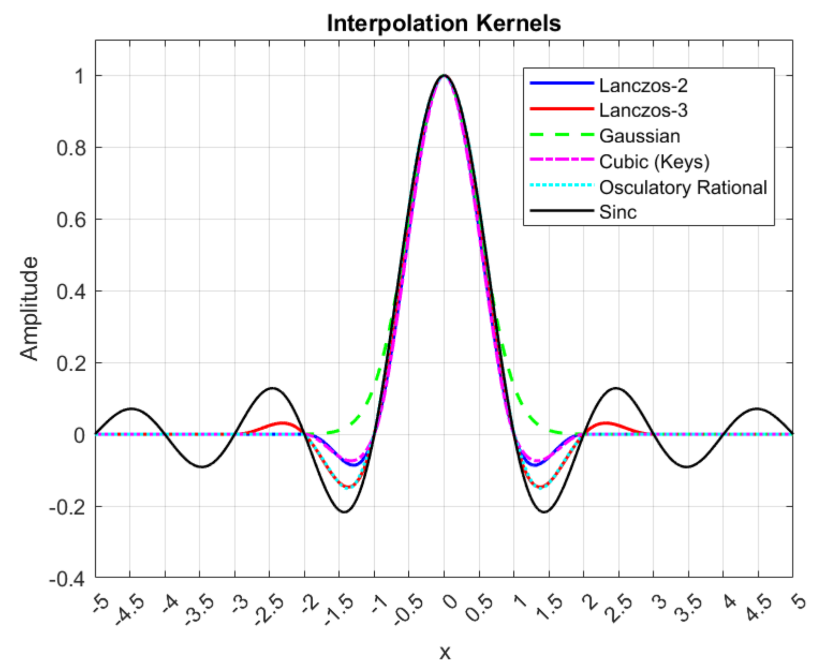
We evaluate how different sampling methods affect the preservation of image information by analyzing their Power Spectral Density (PSD) in comparison to that of the original image. Natural images generally exhibit a 1/f2 PSD distribution, meaning that maintaining low-frequency components is essential for visual fidelity. To quantify information loss, we compute the relative PSD error between the sampled and original images, providing a direct measure of how well each sampling method retains the original frequency content.

$$\text{Error} = \frac{\sum |\text{PSD}_{\text{original}} - \text{PSD}_{\text{sampled}}|}{\sum \text{PSD}_{\text{original}}} = \frac{\sum_{u,v} \left|\hat{S}_I(u,v) - \hat{S}_{I_{avg}}(u,v)\right|}{\sum_{u,v} \hat{S}_I(u,v)}$$

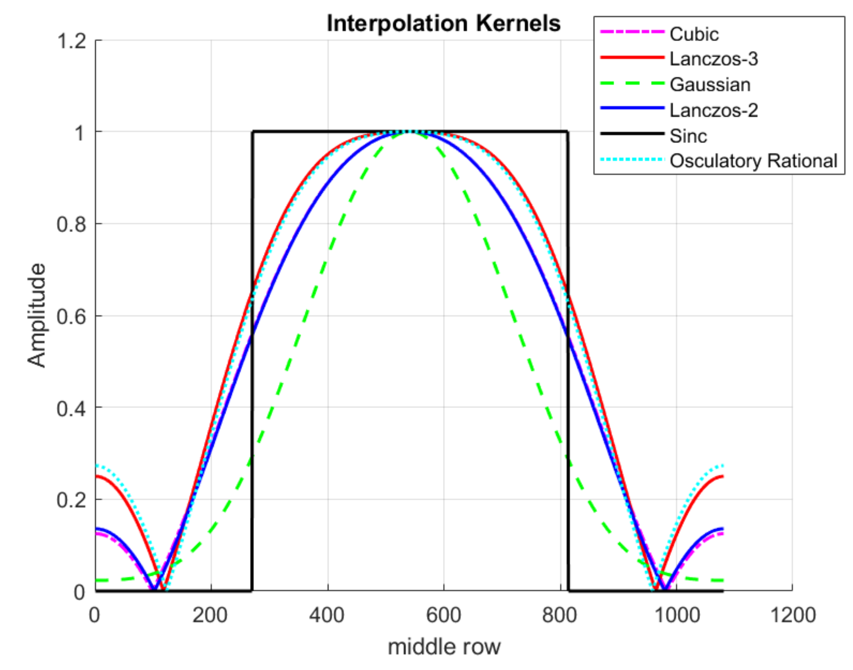
$$S_{\hat{I}(u,v)} = \left|\hat{I}(u,v)\right| = \sqrt{\text{Re}(\hat{I}(u,v))^2 + \text{Im}(\hat{I}(u,v))^2}$$

$$I_{avg}(x,y) = I(x,y) \otimes h \longrightarrow \hat{I}_{avg}(u,v) = F(I(x,y)) \times F(h_{pad}) = \hat{I}(u,v) \times \hat{h}(u,v)$$

$$S_{\hat{I}_{avg}(u,v)} = \left|\hat{I}(u,v) \times \hat{h}(u,v)\right| = \left|\hat{I}(u,v)\right| \times \left|\hat{h}(u,v)\right|$$

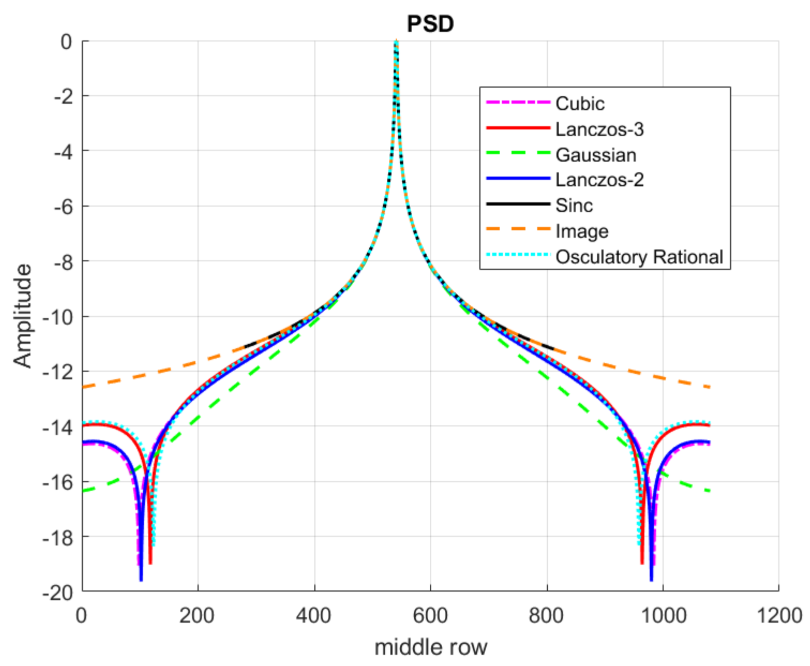


Spatial domain

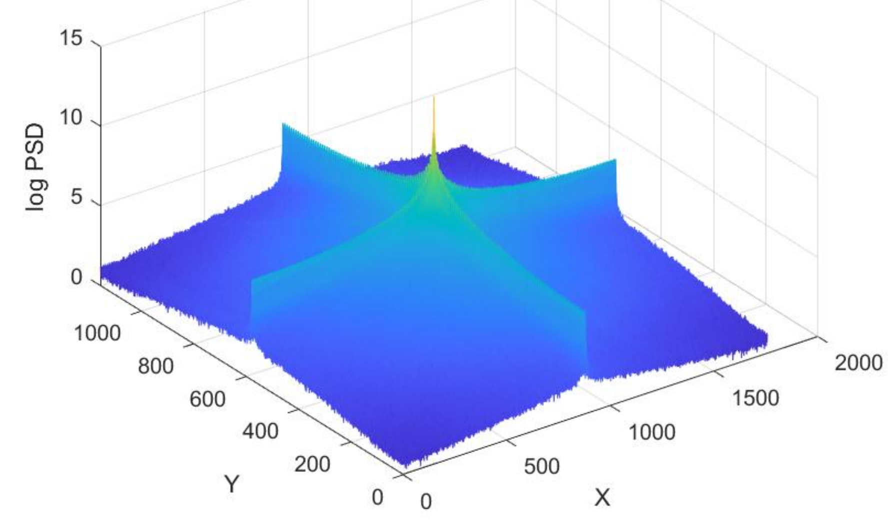


Frequency domain

Result



PSD graph of the sampled Bloch dataset with different interpolation kernels



PSD graph of Bloch dataset

Relative PSD Error of Sampling Kernels on the Bloch Dataset

kernel size	lancsoz2	lancsoz3	cubic	[box]	gaussian	[sinc]	RI
3x3	0.1783	0.1804	0.1776	0.1285	0.1803	**0.0978**	0.182
5x5	0.1543	0.1239	0.1537	0.1285	0.2135	**0.0978**	0.1275

Processing HDR image of Bloch dataset [4] with McCann99 and Jacobi Retinex with two sampling methods

HDR image name	McCann99		Jacobi-box		Jacobi-sinc
	iteration	TMQI	iteration/delta E	TMQI	TMQI
CarWall	16	0.903	10/2.7	0.9099	0.9208
CoffeeShop	16	0.912	16/2.7	0.9151	0.9285
Egyptian	16	0.855	15/2.7	0.8715	0.8831
Engines	32	0.975	20/2.9	0.9764	0.9727
FatCloud	16	0.794	11/2.8	0.8048	0.8082
KitchenWindow	8	0.874	10/2.2	0.8747	0.8918
MansChinese	16	0.852	10/2.7	0.8695	0.8704
Natural_MirrorBall	16	0.878	12/2.3	0.8855	0.909
Popcorn_Counter	16	0.839	12/2.5	0.8381	0.8511
SantaMonica_Sunset	8	0.617	8/2.9	0.6254	0.5961
WalkOfFame	24	0.932	18/2.6	0.9357	0.9372
				0.864	**0.870**

Conclusions and Outlook

- Jacobi version of Retinex is faster than McCann99
- The best kernel for creating a sampling pyramid in our Retinex was the sinc kernel. It preserves the largest portion of low-frequency content resulting in better information retention and improved overall image quality.

References

1. Chandra, A., Acharya, B., Khan, M.I.: Retinex image processing: improving the visual realism of color images. Int. J. Inf. Technol. Knowl. Manag. 4(2), 371–377 (2011)
2. McCann, J.J.: Lessons learned from mondrians applied to real images and colour gamuts. In: CIC pp. 1–8. IS&T (1999)
3. A. Karami and G. D. Finlayson, "Unifying path and center-surround retinex algorithms," in LIM. IST, 2024 (In press).
4. Bloch, C. [2007], The HDRI handbook, Rockynook.