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Adaptive Fractional-order Differentiation for Enhanced Image Contrast Utilizing Caputo Masks

Z. Mortezaie*[a], Z. Amiri[b], M. Mortezaee[c]

[a] Department of Mathematics and Computer Sciences, Hakim Sabzevari University, Sabzevar, Iran
[b] Department of Computer Engineering, University of Science and Technology of Mazandaran, Behshahr, Iran
[c] Faculty of Computer Engineering, Shahrood University of Technology, Shahrood, Iran

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A B S T R A C T

Image enhancement remains a cornerstone in digital image processing, aiming to improve visual clarity through various methods. Spatial domain techniques include integer-order and fractional-order differentiation. Although widely used, traditional integer-order differentiation techniques suffer from limitations such as indiscriminate spatial frequency treatment and noise amplification, leading to degraded image quality. This paper proposes an adaptive fractional-order differentiation approach employing Caputo fractional differential masks to selectively enhance image details. This approach uses image gradient information to determine the appropriate fractional order. By dynamically adjusting the fractional order based on specific image requirements, the method achieves superior contrast improvement while preserving fine details and minimizing noise. Experimental results, evaluated using metrics such as Pratt's Figure of Merit (FOM), Structural Similarity Index (SSIM), and Peak Signal-to-Noise Ratio (PSNR), demonstrate that this approach outperforms comparable techniques, highlighting its effectiveness in image enhancement.

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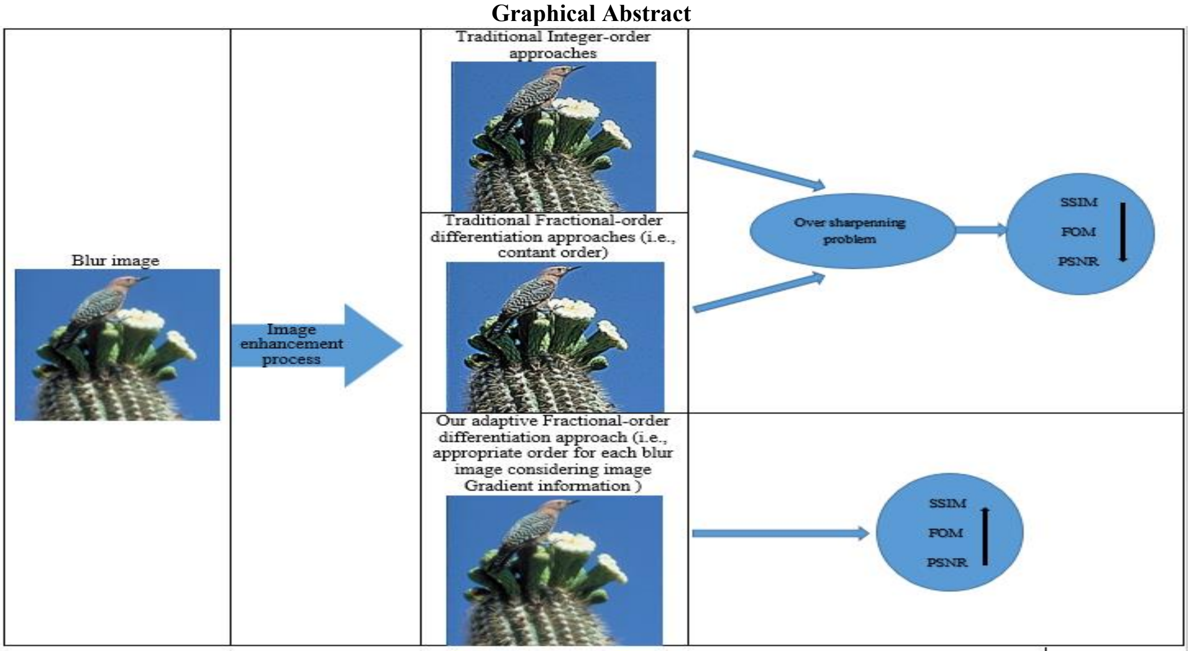
Graphical Abstract



*Corresponding Author Email: zm.mortezaie@gmail.com (Z. Mortezaie)

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1. INTRODUCTION

Digital image processing relies heavily on image enhancement methods because they are fundamental tools for achieving better visual outcomes. Different image refinement techniques have evolved over time, including basic approaches such as histogram equalization (1) and modern methods based on machine learning (2). The two basic enhancement strategies for digital image processing fall under spatial domain methods and techniques from the frequency domain. Spatial domain methods modify pixel values using local filters or masks that affect small clusters of nearby pixels (3). Image enhancement methods using the frequency domain analyze the Fourier transform of images to modify their frequency characteristics (4).

Multiple spatial domain differentiation techniques are used to highlight significant image features through unsharp masking (5), the Laplacian filter (6), the Canny edge detector (7), and anisotropic diffusion (8). First- and second-order derivative-based operations are traditional techniques used for edge detection and sharpening tasks. Integer-order methods have significant performance constraints as their primary limitation. These methodologies fail to discriminate spatial frequencies because they treat all equally, leading to detail loss (9). High-pass filters created with integer-order differentiation processes tend to produce noise increases that degrade image quality (10). Integer-order enhancement techniques demonstrate an inflexible nature that restricts their ability to support diverse image features and enhancement needs (11).

Fractional-order differentiation methods have proven to be viable solutions to address these problems. The use of fractional derivatives expands the pixel area from which information is gathered, leading to a better understanding of extended image dependencies [9]. Fractional-order differentiation offers two important advantages. The first advantage stems from its continuous differentiation order palette, which interlinks integer-order operator functions (12). The computation process using fractional derivatives preserves historical image information, thus maintaining contextual details better (13). Fractional differentiation methods demonstrate impressive capabilities in multiple enhancement operations, including contrast improvement (14), edge detection (15), and texture analysis (14). The fractional-order control enables image enhancement that improves contrast precision while maintaining all fine details. These derivatives provide better performance for edge detection in noisy conditions (15). These derivatives offer significant benefits in texture analysis and segmentation while performing edge detection because they efficiently acquire low-frequency information and high-frequency details (16).

The application of fractional-order differentiation extends numerous benefits, but multiple obstacles remain when implementing it for image enhancement. Strong research demands better theoretical models that explain how fractional derivatives interact with image elements. Scientists work toward improving computational efficiency in fractional derivative implementation processes (17). The research community requires more study to find optimal fractional orders that suit different image enhancement goals (18).

Considering the importance of fractional orders in image enhancement, this paper presents an adaptive fractional-order differentiation method that adjusts the fractional order of the Caputo fractional differential mask (19) according to different image enhancement requirements for various image types.

The contributions of this paper are summarized as follows:

a) This paper fills the research gap through an adaptive fractional-order differentiation approach to enhance images with different contrast levels.
b) The adaptive Caputo fractional-order differential mask is used to enhance various images with different enhancement requirements.
c) To achieve this goal, the gradient information of each image is used to adaptively select the appropriate fractional-order.
d) The performance of our proposed approach is compared with some existing image enhancement methods using FOM, SSIM, and PSNR metrics.

The experimental results show the superiority of the proposed adaptive fractional-order differentiation method compared to other existing image enhancement approaches.

This paper follows the below structure: Section 2 provides a brief review of current image enhancement techniques using fractional-order differentiation approaches. Section 3 explains the Caputo fractional derivative while presenting our adaptive fractional-order differentiation strategy. The manuscript concludes with its findings and conclusion in Sections 4 and 5, respectively.

2. RELATED WORKS

Fractional calculus is used in image processing tasks such as image edge detection (20-29), image enhancement, and de-noising (9, 16, 29-33). This section briefly describes some existing approaches in this field.

Wang et al. (29) proposed an enhancement method that combines fractional-order phase stretch transform (30) with relative total variation (31) to enhance both low and medium image frequencies. The algorithm removes initial image noise through the implementation of low-pass filtering techniques. Edge extraction from the filtered image is achieved through applications of the fractional-order phase stretch transform. Specific edges obtained from this process are reunited with the original image through relative total variation processing to preserve important structures and improve image quality.

The fractional differential-inverse-distance-weighted enhancement algorithm, presented Huang et al. (32), serves as a depth image enhancement algorithm. This method utilizes fractional differentiation to improve the detection of texture and edge qualities for enhanced feature detection. The refinement process and noise management during enhancement occur through the combination of convolution templates with fractional differential operators, which protect important structural details. The algorithm applies a fractional differential-inverse-distance-weighting method to modify pixel values as a function of their relative position to important features and edges.

Ruiyin and Bo (33) demonstrated an image enhancement method by merging fractional calculus with the Retinex theory (34). Fractional differentiation serves to improve image texture before obtaining the final input by preprocessing the initial image. After image preprocessing through a single-scale Retinex algorithm, the method divides images into illumination and reflection elements. The process continues with fractional integration, which performs noise reduction on the reflected components. Contrast Limited Adaptive Histogram Equalization (CLAHE) (35) serves as the last step to boost image contrast levels.

Huang et al. (9) demonstrated how fractional calculus enhanced images while performing de-noising applications. The proposed methodology consists of two concurrent tasks using fractional-order derivative properties to achieve image enhancement and image de-noising capabilities. The method uses fractional-order differential operators as an enhancement mechanism for images. Researchers apply experimental variations to differentiation orders to improve image clarity and enhance edge visibility during the enhancement process. The method implements fractional-order integral operators to perform image de-noising functions.

Jalab and Ibrahim (16) presented a texture enhancement methodology in which incorporated the fractional-order Savitzky-Golay differentiator introduced by Chen et al. (36). Researchers used this technique to upgrade digital images by improving texture visibility without changing the essential image characteristics. The Savitzky-Golay filter receives a generalized form through fractional calculus, employing Srivastava-Owa fractional operators (37). The method applies sliding weight window operations to calculate generalized fractional-order derivatives of images. Applying the fractional-order Savitzky-Golay operator allows the method to improve edges and prominent features present in textures.

Kaur et al. (38) combines fractional Fourier transforms with Riesz fractional derivatives (39) to detect more accurate image edges before using these edges to enhance image quality. This image analysis method utilizes the fractional Fourier transform to process images by preserving spatial and frequency data points simultaneously. Image edges are extracted through the application of Riesz fractional derivatives following image transformation. The quality improvement process reintegrates edges derived from Riesz fractional derivatives into the original image.

Mortazavi et al. (40) described how fractional derivatives were incorporated into sparse representation methods to achieve image resolution enhancement. The method utilizes fractional derivative mathematical properties to make super-resolved images more detailed by better preserving image information. This method enhances images by extracting dictionaries from low-resolution images to create high-resolution images. Fractional derivatives integrated into the proposed method help improve the representation of image characteristics.

Azarang and Ghassemian (41) integrated panchromatic (PAN) and multispectral (MS) images via fractional-order differentiation methods for image fusion. The purpose of this method is to improve both quality and details in the merged images for multiple remote sensing applications. The procedure starts by loading entire PAN and MS image collections from the dataset. As a first step in image fusion, the data requires preprocessing through both down-sampling and normalization techniques. The main concept of this method requires producing fractional-order differentiations. This operation generates a superimposed filter which extracts necessary image features from the original data. A primitive detail map generation procedure occurs for each spectral band of MS images through this method. The map indicates essential image characteristics vital for analytic purposes. The superimposed mask, which has been generated, applies onto the primitive detail maps to perform additional refinement. The process produces one fused image which unites PAN image high-resolution details with the spectral information of MS images.

Motłoch et al. (13) developed an approach to upgrade fused images by implementing fractional derivative techniques. Fractional-order derivatives are used to increase specific details during image fusion processes. This approach utilizes eight-directional non-integer order filters which extract directional attributes from data. The method consolidates PAN and MS image data through fractional-order derivative masks which extract intricate characteristics from each image type. The computational efficiency increases through Fast Fourier Transform (FFT) that executes fractional-order derivative approximation in the frequency domain, leading to effective image characteristic manipulation.

Nchama et al. (42) presented an algorithm that effectively improves image contrast through fractional calculus technique by applying the Caputo-Fabrizio fractional differential mask found by Caputo and Fabrizio (43). The technique provides regulated image contrast improvement because users can modify the fractional differential order as needed to personalize the enhancement operation. The proposed mask delivered the best contrast results after being used with a fractional order value of 10^{-10}.

Most of the examined methods fail to recognize how fractional orders affect image enhancement results. This paper fills the research gap through an adaptive fractional-order differentiation approach to enhance images with different contrast levels. The developed image enhancement method uses Caputo fractional differential masks whose fractional order depends on the necessary degree of contrast adjustment for diverse image categories (10, 44-54).

3. PROPOSED METHOD

3. 1. Fractional-Order Differentiation Fractional-order differentiation offers unique benefits in image enhancement through its ability to provide a wide spectrum of differentiation orders between integers. Image processing algorithms become more flexible through the use of fractional-order differentiation systems because this property surpasses traditional integer-order methods. The use of fractional-order differentiation provides multiple stable approaches applicable to image enhancement. Multiple acceptable frameworks emerged from mathematicians seeking to utilize the capabilities of this method despite its undefined standardized definition. Image processing utilizes three main definitions for fractional differentiation: Grunwald-Letnikov (G-L) (55), Riemann-Liouville (R-L) (56), and Caputo (19). The fundamental concept of integer-order differentiation supports the G-L definition to enhance edge detection and feature extraction processes. The R-L definition performs well at image pattern detection via its integer-order integration foundation to analyze fragile image features. The Caputo definition, derived from integer-order integration, finds practical uses in real-world modeling and can serve as an effective tool for adaptive image enhancement techniques.

Although fractional-order differentiation is increasingly used in image processing, the vast majority of related studies focus on the G-L and R-L definitions. In contrast, the Caputo derivative has received relatively limited attention in image processing applications. Therefore, in our proposed adaptive fractional-order differentiation approach, the Caputo derivative is employed to demonstrate its potential in image enhancement. Furthermore, the proposed adaptive strategy can be applied to other fractional definitions, helping to expand the scope of adaptive fractional-order techniques in image processing.

3. 2. Caputo Definition The Caputo fractional differentiation of the function v with respect to t of order α is defined as Equation 1 (19):

$$D^{\alpha}v(t) = \frac{1}{\Gamma(1-\alpha)}\int_0^t \frac{v'(\mathcal{T})}{(t-\mathcal{T})^{\alpha}}\,d\mathcal{T}, 0 < \alpha \leq 1. \quad (1)$$

The finite difference approximations for the Caputo fractional derivative are provided as follows. The time interval $[0,T]$ is divided into M equal subintervals, resulting in a step size $\delta t = \frac{T}{M}$. The time points is denoted as $t_k = k\delta t$ where $k = 0, 1, \dots, M$ and let $v_k = v(t_k)$. The Caputo derivative in Equation 1 at $t = t_k$ can be approximated as Equation 2:

$$D^{\alpha}v(t_k) = \frac{1}{\Gamma(1-\alpha)}\sum_{j=1}^{k}\int_{t_{j-1}}^{t_j}(t_k-\mathcal{T})^{-\alpha}\frac{\partial v(\mathcal{T})}{\partial \mathcal{T}}\,d\mathcal{T} \approx \frac{1}{\Gamma(1-\alpha)}\sum_{j=0}^{k}\frac{v_j - v_{j-1}}{\delta t}\int_{t_{j-1}}^{t_j}(t_k-\mathcal{T})^{-\alpha}\,d\mathcal{T}. \quad (2)$$

The integral shown in Equation 2 is computed as Equation 3:

$$\int_{t_{j-1}}^{t_j}(t_k-\mathcal{T})^{-\alpha}\,d\mathcal{T} = \frac{\delta t^{(1-\alpha)}}{1-\alpha}\left[(k-j+1)^{(1-\alpha)} - (k-j)^{(1-\alpha)}\right], \quad (3)$$

Considering $\omega_{\alpha} = \frac{(\delta t)^{-\alpha}}{\Gamma(2-\alpha)}$ and $\varpi_{\alpha,j} = (j+1)^{1-\alpha} - j^{1-\alpha}$, the discretized form of the Caputo fractional derivative is as Equation 4:

$$D_t^{\alpha}v_k \approx \omega_{\alpha}\left[v_k - v_{k-1} + \sum_{j=1}^{k-1}\varpi_{\alpha,j}\left(v_{k-j} - v_{k-j-1}\right)\right], k = 1, \dots, M. \quad (4)$$

Note that, in image processing, δt should be set to 1, as the smallest scale is one pixel. Differentiating the continuous function $v(t)$ with respect to t allows us to express the difference formula for the fractional differentiation of $v(t)$ as shown in Equation 4.

In this context, j is obtained based on the function and indicates the j-th neighborhood value. For easier calculations, Equation 4 is extended to two dimensions, and for $j=1$ Equations 5 and 6 are obtained as follows:

$$D_x^{\alpha}v(x,y) = \frac{1}{\Gamma(2-\alpha)}\left[v(x,y) + (2^{1-\alpha}-2)v(x-1,y) - \left(2^{(1-\alpha)}-1\right)v(x-2,y)\right] \quad (5)$$

$$D_y^{\alpha}v(x,y) = \frac{1}{\Gamma(2-\alpha)}\left[v(x,y) + (2^{1-\alpha}-2)v(x,y-1) - \left(2^{(1-\alpha)}-1\right)v(x,y-2)\right] \quad (6)$$

The implementation of anti-rotation abilities in image processing requires developers to integrate several directional masks thoughtfully because this process presents multiple challenges. These special fractional differentiation masks operate on both horizontal (x-axis) and vertical (y-axis) directions, enabling systematic detection and compensation of input image rotational changes.

Let $k_1 = \frac{1}{\Gamma(2-\alpha)}$, $k_2 = \frac{(2^{(1-\alpha)}-2)}{\Gamma(2-\alpha)}$, and $k_3 = \frac{(2^{(1-\alpha)}-1)}{\Gamma(2-\alpha)}$, denote the horizontal, vertical, and cross-directional fractional differentiation masks, respectively. The eight distinct masks represented in Figure 1 correspond to various directional orientations: the positive x-direction (Figure 1(a)), positive y-direction (Figure 1(b)), negative x-direction (Figure 1(c)), negative y-direction (Figure 1(d)), left upper diagonal (Figure 1(e)), left lower diagonal (Figure 1(f)), right upper diagonal (Figure 1(g)), and right lower diagonal (Figure 1(h)).

Masks form the foundation for developing the end product of an anti-rotation mask. A configuration as shown in Figure 2 emerges after performing partial fractional differentiation within each of the eight separate orientations. To complete the procedure we need weight normalization for each element of the combined mask by performing a total sum division of all its components. The normalization method guarantees that every directional component creates an identical influence on the end results. By employing this combined approach, the system obtains simultaneous multi-perspective imaging evaluation, which improves its capacity to detect subtle variations and retain critical image details.

3. 3. Proposed Image Enhancement Approach

The implementation of the Caputo fractional differential mask depicted in Figure 2 improves image quality as it convolves with low contrast images. Image quality is significantly enhanced only through selecting the proper value of the fractional order parameter (α). The graphical representation in Figure 3 shows how contrasting image elements change with different fractional order inputs.

0	k_1	0
0	k_2	0
0	k_3	0

(a) Positive x-coordinate

0	0	0
k_1	k_2	k_3
0	0	0

(b) Positive y-coordinate

0	k_3	0
0	k_2	0
0	k_1	0

(c) Negative x-coordinate

0	0	0
k_3	k_2	k_1
0	0	0

(d) Negative y-coordinate

k_3	0	0
0	k_2	0
0	0	k_1

(e) Left upper diagonal

0	0	k_1
0	k_2	0
k_3	0	0

(f) Left lower diagonal

0	0	k_3
0	k_2	0
k_1	0	0

(g) Right upper diagonal

k_1	0	0
0	k_2	0
0	0	k_3

(h) Right lower diagonal

Figure 1. The eight distinct masks in different directional orientations

This figure contains an original input image in part (a) which looks blurry, followed by images (b) through (d) that depict the processed data after using the Caputo fractional differential mask together with three different fractional order procedures, including low, high, and optimal settings. The specified visualizations display how fractional order variations produce considerable effects on image clarity and their contrast capacity. Using a low fractional order imposes more blurriness on the input image, while a high fractional order causes an over-sharpening issue.

Based on the aforementioned points, in this section, we propose a novel adaptive fractional-order differentiation technique designed to enhance image contrast. The proposed method adaptively adjusts the fractional order of the Caputo fractional differential mask in accordance with the required level of enhancement for blur images. In our proposed approach, using Equation 7, the input image is convolved separately with 20 different Caputo fractional differential masks considering 20 different fractional orders from 0.01 to 1, at intervals of 0.5, resulting in 20 different convolved images. Then, the gradient variation of each convolved image compared with the input image is computed using Equations 8 and 9:

$$C(x, y) = I(x, y) * M, \tag{7}$$

$$G(x, y) = I(x, y) - C(x, y), \tag{8}$$

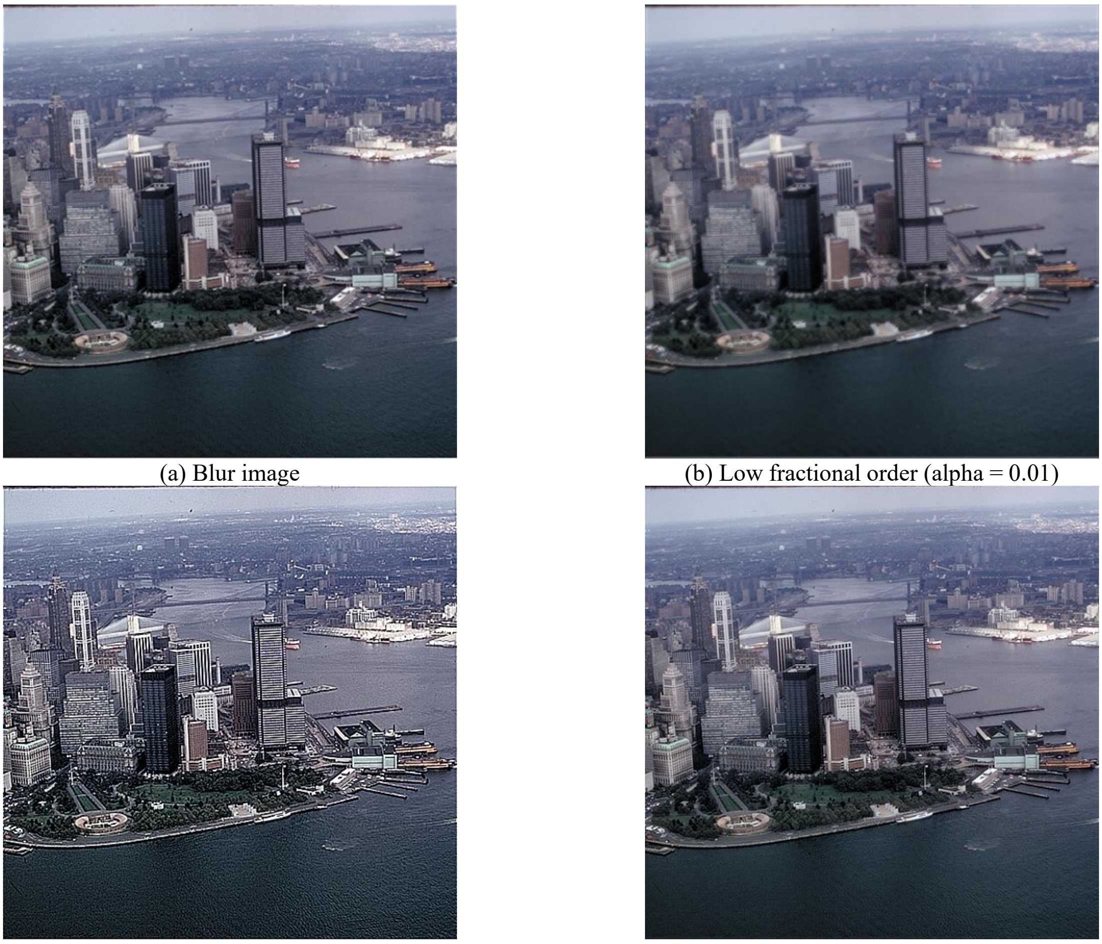
$$\|G\|_n = \left(\sum_{x,y} |G(x, y)|^n\right)^{\frac{1}{n}}, \tag{9}$$

where M and $*$ respectively denote the Caputo fractional differential mask shown in Figure 2 and the convolution operator; $I(x, y)$, $C(x, y)$, and $G(x, y)$ respectively represents an input image, convolved image, and gradient image. Also, $|\,.\,|$ and $\|\,.\,\|_n$ symbols are the absolute value and l_n norm respectively.

Our analysis indicates that weak edges and details can be more effective than strong ones in determining the optimal fractional order. Hence, the proposed method aims to enhance the influence of weak edges and details compared to stronger ones during the fractional order selection process. We determine the $l_{0.8}$ norm of gradient information through the input exponent value n equal to 0.8 in Equation 9. This approach allows us to balance the contribution of both strong and weak details in determining the optimal fractional order.

k_3	0	k_3	0	k_3
0	k_2	k_2	k_2	0
k_3	k_2	$8 \times k_1$	k_2	k_3
0	k_2	k_2	k_2	0
k_3	0	k_3	0	k_3

Figure 2. The final mask constructed by combining eight distinct masks shown in Figure 1



(a) Blur image (b) Low fractional order (alpha = 0.01)

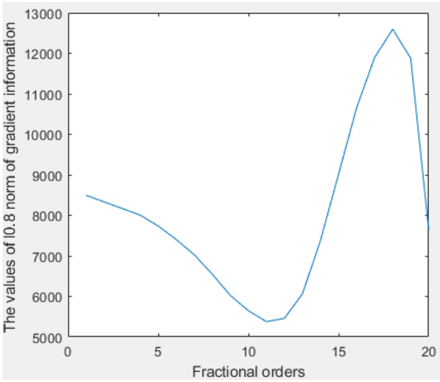
(c) High fractional order (alpha = 0.9) (d) Appropriate fractional order (alpha = 0.7)

Figure 3. The results of convolving the input image with Caputo fractional differential mask using different fractional order

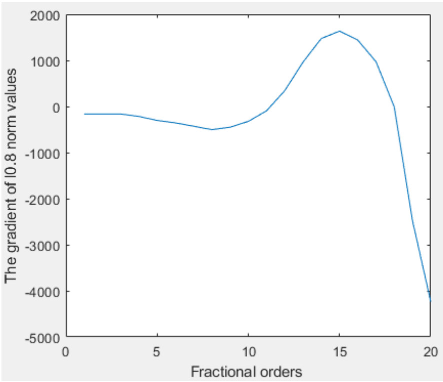
The analysis of the $l_{0.8}$ norm of gradient information for 20 fractional orders on one instance image is displayed in Figure 4. The values of $l_{0.8}$ norm of gradient information exist in Figure 4(a) that displays results across the 20 evaluated fractional orders. The gradient of these 20 obtained $l_{0.8}$ norm values appears in Figure 4(b) while using similar axis representations.

The initial 11 fractional orders appear to cause image blurring based on Figures 4(a) and 4(b) as they decrease both $l_{0.8}$ norm values and their gradients according to the data. The application of such orders leads to deterioration of image details while producing overall image blurring. The 12th through 18th fractional orders generate rising trends for both $l_{0.8}$ norm values and their gradients. The image enhancement process of these intermediate orders works better because they enhance contrast simultaneously with detail retention. The $l_{0.8}$ norm values and their gradients both decrease when used with the 19th and 20th fractional orders thus potentially causing deterioration of image quality. Elevated fractional orders past specified values can cause over-sharpening problems in digital images.

Our proposed approach will choose the best fractional order from the 12th to 18th fractional orders because of these discovered results. The targeted fractional order interval includes various values which without significant impact on image quality alongside those that trigger undesirable sharpening effects. Hence, we use the gradient of $l_{0.8}$ norm values to select the optimal fractional order which results in the maximum increase of $l_{0.8}$ norm values in our proposed adaptive selection method. We use this fractional order for enhancing contrast because it delivers optimal results without creating over-sharpening artifacts. Note that these observations and analysis pertain to an instance input image. Hence, in our proposed approach, a similar manner is generalized across various input images. This approach allows our method to adaptively adjust the degree of enhancement based on the inherent characteristics of each image, potentially leading to more consistent and desirable results across various types of visual content.



(a) The values of $l_{0.8}$ norm of gradient information for 20 different fractional orders



(b) The gradient of 20 obtained $l_{0.8}$ norm values

Figure 4. The values of $l_{0.8}$ norm of gradient information for different fractional orders and their gradient

4. EXPRIMENTAL RESULTS

We subjectively and objectively evaluate the effectiveness of our adaptive fractional-order differentiation method in this section. Three objective metrics serve this analysis: Pratt's Figure of Merit (FOM) (57, 58), the Structural Similarity Index Metric (SSIM) (59, 60), and the Peak Signal-to-Noise Ratio (PSNR) (61). The outcomes for both FOM and SSIM are expressed as values ranging from 0 to 1. Higher values in these three metrics indicate greater similarity between the two images.

The experiment relies on the CSIQ database (62), which contains 30 reference images with different degrees of Gaussian blur. The reference image collection comprises five progressively blurred versions, classified from level 1 to level 5. Blur intensity increases as the levels progress from 1 to 5, while high-frequency elements experience progressively worse degradation, particularly involving edge components. Images become unreadable in terms of edge definition at levels 4 and 5 because edge degradation reaches high levels. Our proposed approach shows reduced effectiveness when combating blurriness at higher reference image levels because it primarily focuses on edge extraction tasks. Therefore, our proposed adaptive fractional-order differentiation method was applied to all 90 potential blurred images at levels 1, 2, and 3 for evaluation.

We compare our approach with results derived from the Caputo fractional differential mask, using three distinct fractional order values: 0.01, 0.6, and 0.9. The mean values and variances for FOM, SSIM, and PSNR obtained from these approaches are summarized in Table 1. As indicated in the table, significant differences are observed in the mean values of FOM, SSIM, and PSNR among the various approaches. Specifically, the imposed blurriness caused by a low fractional order (0.01) leads to insufficient detail, while excessive sharpening with a high fractional order (0.9) and the use of a constant fractional order value (0.6) across all input images—without adapting to specific enhancement needs—results in reduced mean values for FOM, SSIM, and PSNR. It is evident that the mean FOM, mean SSIM, and mean PSNR for our adaptive fractional-order differentiation approach outperform those of the comparative approaches.

In Table 2, we compare our proposed approach with image enhancement approaches proposed by Huang et al. (9) and Nchama et al. (42), which are based on fractional calculus, as well as with integer-order differentiation approaches, namely, classic un-sharp masking (5) and the Laplacian filter (6). The image enhancement techniques described by Huang et al. (9) and Nchama et al. (42) used constant fractional order values for their fractional differential masks without considering specific enhancement requirements. Classic un-sharp masking and the Laplacian filter operate on image enhancement without adapting to the particular level of enhancement needed. In classic un-sharp masking, first, the edge information of the input image is extracted by subtracting a blurred version of the image from the original image.

TABLE 1. Performance Comparison of the Proposed Method with the Caputo fractional differential mask using different alpha

	Blur images	Our adaptive fractional-order differentiation approach	Caputo fractional differential mask using different alpha		
			alpha = 0.01	alpha = 0.6	alpha = 0.9
FOM Mean	0.8742	**0.9010**	0.7255	0.8447	0.8839
SSIM Mean	0.9346	**0.9472**	0.8449	0.9362	0.8051
PSNR Mean	32.6389	**32.4978**	26.9026	31.6691	23.7734

TABLE 2. Comparison of the Proposed Method with Fractional and Integer-Order Image Enhancement Techniques.

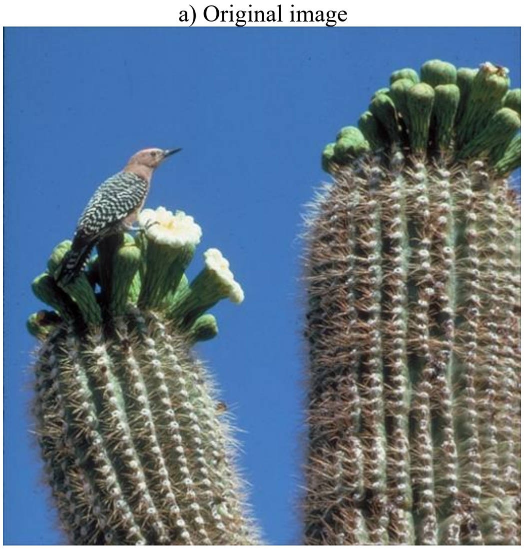
	Blur images	Our proposed approach	The method proposed in (9)		The method proposed in (42)		Un-sharp masking (5)		Laplacian filter (6)	
FOM Mean	0.8742	**0.9010**		0.8257		0.8630		0.8619		0.8501
SSIM Mean	0.9346	**0.9472**	alpha = 1.5	0.8488	alpha = 0.5	0.7353	landa = 0.1	0.7117	alpha = 1	0.9192
PSNR Mean	32.6389	**32.4978**		27.6965		20.4225		20.6360		30.7600

Then, a parameter named gain factor (lambda) is used to scale the extracted edges before adding them to the original image. Additionally, the Laplacian filter highlights image edge information using a second-order derivative, with a scaling coefficient (alpha) controlling the level of edge enhancement. The performance of both methods depends on the proper tuning of these coefficients to avoid over-sharpening and noise amplification. Considering these points, our proposed method achieves superior mean FOM, along with higher mean SSIM and mean PSNR values, when compared to other methods based on Table 2.

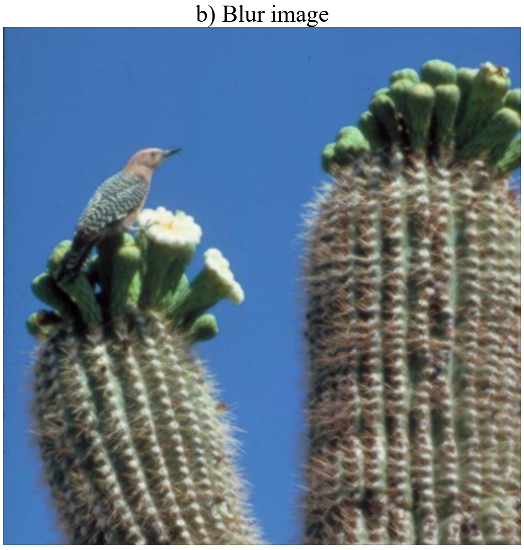
Figures 5 to 8 present four instances demonstrating the effectiveness of our proposed approach when compared to results obtained from the Caputo fractional differential mask, utilizing three different fractional order values: 0.01, 0.6, and 0.9, as well as classic un-sharp masking (5), the Laplacian filter (6), and the methods

a) Original image

b) Blur image



c) Our adaptive fractional-order differentiation approach



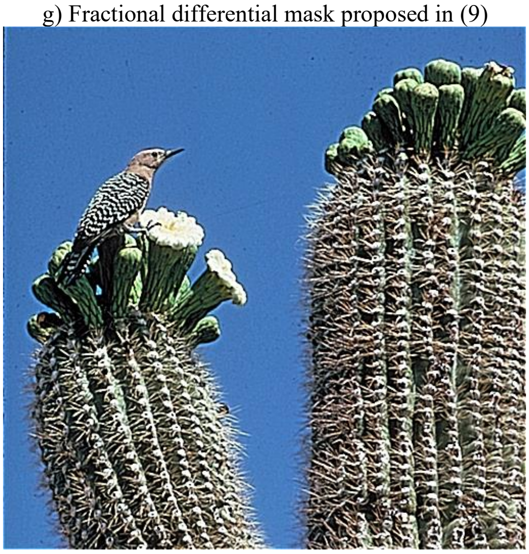
d) Caputo fractional differential mask using alpha = 0.01

e) Caputo fractional differential mask using alpha = 0.6

f) Caputo fractional differential mask using alpha = 0.9

g) Fractional differential mask proposed in (9)

h) Laplacian filter (6)



i) Fractional differential mask proposed in (42)

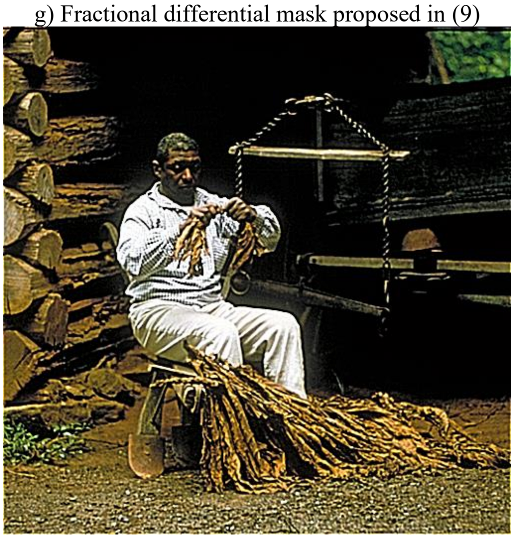
j) Un-sharp masking (5)

Figure 5. Results obtained from our adaptive fractional-order differentiation approach, the Caputo fractional differential mask using three distinct values for fractional order as 0.01, 0.6, and 0.9, classic un-sharp masking and the laplacian filter, as well as the methods proposed by Huang et al. (9) and Nchama et al. (42).

a) Original image
b) Blur image
c) Our adaptive fractional-order differentiation approach
d) Caputo fractional differential mask using alpha = 0.01
e) Caputo fractional differential mask using alpha = 0.6
f) Caputo fractional differential mask using alpha = 0.9

g) Fractional differential mask proposed in (9)

h) Laplacian filter (6)



i) Fractional differential mask proposed in (42)

j) Un-sharp masking (5)

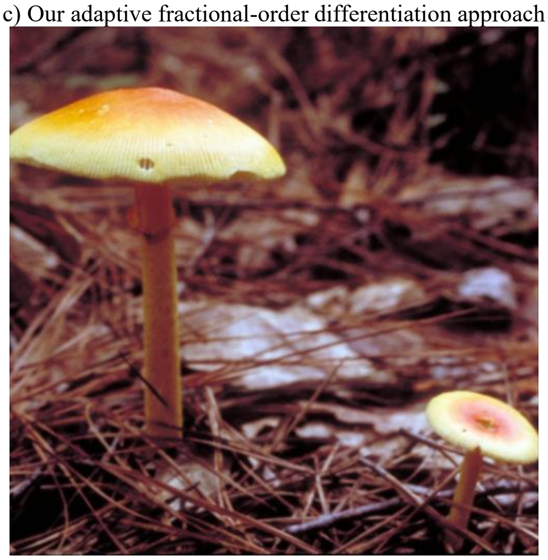
Figure 6. Results obtained from our adaptive fractional-order differentiation approach, the Caputo fractional differential mask using three distinct values for fractional order as 0.01, 0.6, and 0.9, classic un-sharp masking and the laplacian filter, as well as the methods proposed proposed by Huang et al. (9) and Nchama et al. (42).

a) Original image

b) Blur image

c) Our adaptive fractional-order differentiation approach

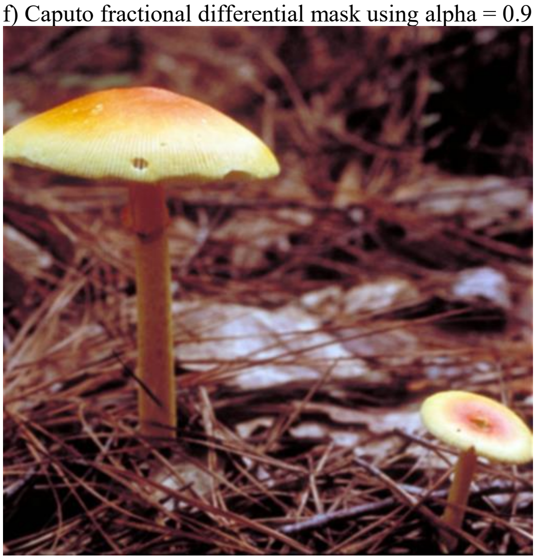
d) Caputo fractional differential mask using alpha = 0.01



e) Caputo fractional differential mask using alpha = 0.6

f) Caputo fractional differential mask using alpha = 0.9

g) Fractional differential mask proposed in (9)



h) Laplacian filter (6)

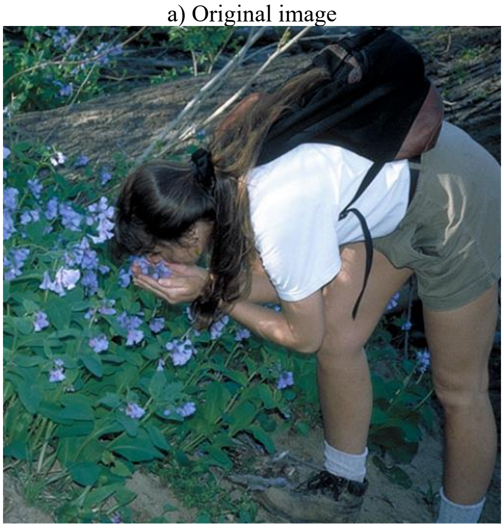
i) Fractional differential mask proposed in (42)

j) Un-sharp masking (5)

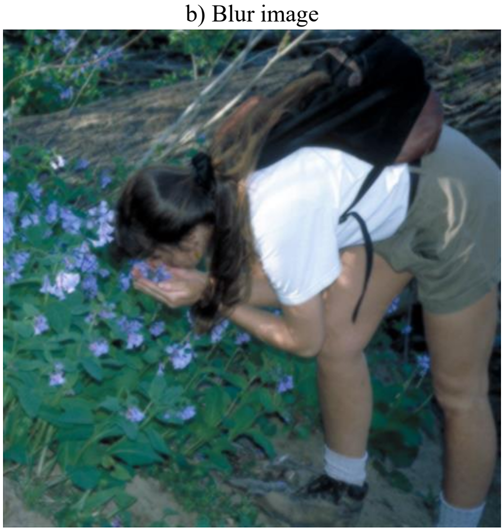
Figure 7. Results obtained from our adaptive fractional-order differentiation approach, the Caputo fractional differential mask using three distinct values for fractional order as 0.01, 0.6, and 0.9, classic un-sharp masking and the laplacian filter, as well as the methods proposed by Huang et al. (9) and Nchama et al. (42).

a) Original image

b) Blur image



c) Our adaptive fractional-order differentiation approach



d) Caputo fractional differential mask using alpha = 0.01


e) Caputo fractional differential mask using alpha = 0.6


f) Caputo fractional differential mask using alpha = 0.9


g) Fractional differential mask proposed in (9)


h) Laplacian filter (6)


i) Fractional differential mask proposed in (42)

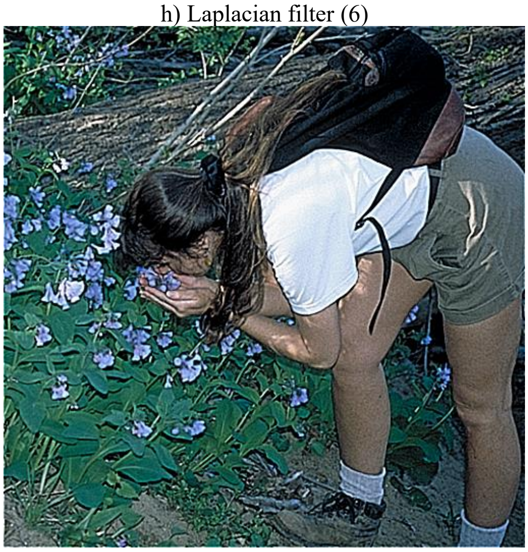

j) Un-sharp masking (5)

Figure 8. Results obtained from our adaptive fractional-order differentiation approach, the Caputo fractional differential mask using three distinct values for fractional order as 0.01, 0.6, and 0.9, classic un-sharp masking and the laplacian filter, as well as the methods proposed by Huang et al. (9) and Nchama et al. (42).

proposed by Huang et al. (9) and Nchama et al. (42). The images enhanced by our adaptive fractional-order differentiation approach are noticeably more visually appealing. In contrast, using a low fractional order of 0.01 in the Caputo fractional differential mask results in significant degradation of the original images, introducing unwanted blurriness. Additionally, fixing the fractional order at 0.6 does not generate sufficient quality improvement in the processed images. A high fractional order value of 0.9 produces image degradations through excessive image sharpening, which leads to reduced quality standards. Traditional integer-order differentiation techniques such as classic un-sharp masking and the Laplacian filter, along with the methods introduced by Huang et al. (9) and Nchama et al. (42) based on fractional calculus, fail to yield appropriate image improvements since they do not consider individual image enhancement needs.

The research details the FOM, SSIM, PSNR values, together with fractional order (alpha) parameters for individual instance images in Table 3. Our method adaptively selects varying fractional order values to enhance each individual image according to its particular requirements as shown in the provided table. Our adaptive fractional-order differentiation method obtains superior FOM, SSIM, and PSNR metrics than alternative approaches in objective performance measurements.

TABLE 3. Performance Analysis of FOM, SSIM, and PSNR with Adaptive Fractional Order Selection across Samples.

		Blur images	**Our proposed approach**		**Caputo fractional differential mask using**			**The method proposed in [9]**	**The method proposed in [42]**	**Un-sharp masking [5]**	**Laplacian filter [6]**
					alpha = 0.01	**alpha = 0.6**	**alpha = 0.9**				
Sample 1	FOM	0.9439	**alpha = 0.66**	**0.9507**	0.7958	0.9209	0.9246	0.8898	0.9017	0.8968	0.9208
	SSIM	0.9693		**0.9879**	0.8665	0.9753	0.8100	0.8890	0.7271	0.7054	0.9523
	PSNR	32.2237		**34.9588**	25.9124	32.1919	20.0057	26.9347	17.1096	16.9060	30.3252
Sample 2	FOM	0.9130	**alpha = 0.71**	**0.9548**	0.7404	0.8835	0.9355	0.8636	0.9093	0.9077	0.8870
	SSIM	0.9532		**0.9861**	0.8494	0.9558	0.8618	0.8842	0.7603	0.7569	0.9357
	PSNR	32.3221		**35.9164**	27.5238	32.0002	23.9633	28.9682	19.6990	19.9957	31.0927
Sample 3	FOM	0.8978	**alpha = 0.81**	**0.9746**	0.7877	0.8696	0.9454	0.8715	0.8996	0.9044	0.8809
	SSIM	0.9425		**0.9766**	0.8863	0.9355	0.9425	0.9206	0.8457	0.8611	0.9354
	PSNR	32.2531		**36.2001**	28.6382	31.2041	29.7402	30.8415	23.1100	24.4652	31.5638
Sample 4	FOM	0.8893	**alpha = 0.76**	**0.9846**	0.7149	0.8582	0.9224	0.8308	0.8943	0.8897	0.8809
	SSIM	0.9294		**0.9827**	0.8156	0.9341	0.8381	0.8519	0.7082	0.7005	0.9354
	PSNR	32.2852		**37.3249**	27.8072	31.8246	24.7817	29.3481	20.0606	20.5089	31.5638

Our proposed adaptive fractional-order differentiation approach can be applied to various computer vision applications. In sports scene analytics, it can be used as a powerful pre-processing step for enhancing the visual quality of frames in cricket-related tasks, such as batting shot classification (63) and umpire signal recognition (64), by improving edge and contrast information. Furthermore, in traffic scene analysis (65), the method can be used to enhance the visibility of vehicles, road signs, and lane markings in images. Beyond these applications, the proposed approach is also applicable in medical imaging (66), remote sensing (41), and surveillance systems (67), where adaptive enhancement can help reveal subtle features.

As mentioned before, in the proposed method, the appropriate fractional order is adaptively selected for each image based on its gradient information. Consequently, the method shows reduced effectiveness when processing images with extremely low-gradient information. To address this limitation, future work may involve combining gradient information with other image cues, such as entropy, or developing contrast-aware boosting strategies to stabilize performance under such conditions. Additionally, the proposed adaptive approach can be extended to other fractional-order differentiation methods such as Grünwald–Letnikov (G-L) and Riemann–Liouville (R-L), potentially improving their performance in image enhancement tasks.

5. CONCLUSION

This paper presents the key advantages of adaptive fractional-order differentiation techniques for image enhancement, addressing the limitations of conventional integer-order methods. Our approach employs a Caputo fractional differential mask while dynamically adjusting the fractional order for each image, thereby enhancing visual quality, preserving critical details, and reducing noise amplification. Experimental results demonstrate that our method outperforms traditional techniques, confirming the significant potential of fractional-order differentiation in image processing applications.

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Persian Abstract

چکیده

ایجاد بهبود در کیفیت تصاویر یکی از ارکان‌های مهم پردازش تصویر دیجیتال محسوب می‌شود که هدف آن افزایش وضوح بصری تصویر از طریق روش‌های عملیاتی مختلف است. در حوزه مکان، از دو تکنیک محبوب برای بهبود کیفیت تصاویر استفاده می‌شود که شامل روش‌های مشتق‌گیری با مرتبه صحیح و مشتق‌گیری با مرتبه کسری است. تکنیک‌های سنتی مشتق‌گیری با مرتبه‌ی صحیح، با وجود کاربرد گسترده خود، از محدودیت‌هایی نظیر عدم تمایز در رفتار فرکانس‌های فضایی و افزایش نویز رنج می‌برند که منجر به کاهش کیفیت تصویر می‌شود. این مقاله رویکردی بر اساس مشتق‌گیری با مرتبه کسری معرفی می‌کند که از ماسک‌های مشتق کسری کاپوتو برای تقویت جزئیات تصویر استفاده می‌کند. در این رویکرد، اطلاعات گرادیان تصویر برای تعیین مرتبه کسری مناسب استفاده می‌شود. با تنظیم پویای مرتبه کسری بر اساس میزان بهبود کیفیت مورد نیاز در هر تصویر، ضمن حفظ جزئیات تصویر و کاهش نویز، کیفیت تصویر بهبود می‌یابد. نتایج آزمایشگاهی با استفاده از معیارهایی ارزیابی مختلف نشان می‌دهد که رویکرد پیشنهادی این مقاله نسبت به سایر روش‌های مورد مقایسه عملکرد بهتری در بهبود کیفیت تصاویر دارد.