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An Efficient on Scale and Structure Aware Image Smoothening for Watermarked Images with Denoising in Improved DCNN– A Review

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Abstract
This research explores novel approaches to image smoothening through the integration of Deep Convolutional Neural Networks (CNN) and Interactive Segmentation techniques. The objective is to enhance image quality by reducing noise and artifacts while preserving important details. We propose a deep learning model that leverages the power of CNNs to automatically learn and adapt image features for effective smoothening. Additionally, interactive segmentation is incorporated to involve user input, allowing for personalized control over the smoothening process. Experimental results demonstrate significant improvements in image quality metrics, indicating the effectiveness of the proposed method. The combination of deep learning and interactive segmentation offers a promising solution for image enhancement, with potential applications in various domains such as medical imaging, computer vision, and photography.
Keywords:Deep Learning; Image Processing; Semantic Segmentation; Medical Image Segmentation; Interactive Refinement; Deep Image Smoothing; CNN-based Smoothening; SegmentationRefinement; Deep Learning for Image Quality Improvement; Image Denoising; Fine-tuning for Segmentation; Neural Network-based Smoothing; Deep Image Analysis; Image Post-Processing

1. Introduction:

In the realm of image processing, enhancing visual quality while maintaining important details is a crucial challenge. Image smoothening techniques play a pivotal role in achieving this balance by mitigating noise and artifacts that can detract from the overall visual appeal. Traditional methods often face limitations in adaptability and effectiveness, particularly when confronted with diverse image content.This research aims to address these challenges by proposing a novel approach that integrates Deep Convolutional Neural Networks (CNN) and Interactive Segmentation techniques for image smoothening. Deep CNNs have demonstrated remarkable capabilities in learning intricate features from data, making them well-suited for image processing tasks. Additionally, the incorporation of interactive segmentation empowers users to actively participate in the smoothening process, providing a more personalized and adaptable solution.Many image processing schemes focus on retrieving structures in images, but there is a lack of proposals that maintain image texture. Current image smoothing schemes do not consider image scale, leading to texture mismatch when scale is changed. Preserving image texture while altering scale remains an open problem, with potential solutions involving interactive segmentation and user input during texture smoothing operations.

2. Related works:

AUV-Net embeds 3D surfaces into a 2D UV space, mapping semantic parts of different shapes to the same location for aligned textures. Texture alignment is learned unsupervised using a simple module inspired by linear subspace learning [1].The study introduces a blind decontouring network (BDCN) to address the blind decontouring problem. It includes flat region detection module (FDM) and decontouring module (DCM)[2].The authors introduce the truncated Huber penalty function, highlighting its flexibility under different parameter settings. A generalized framework incorporating this function is proposed, achieving diverse smoothing behaviors and surpassing previous methods in performance for tasks like image enhancement and artifact removal. The framework is capable of various applications and excels in challenging scenarios [3].Authors propose a method for recovering geometric detail from a single facial image by painting occluded parts, generating textures, and building a multi-view dataset. They use an implicit signed distance function and a renderer to reconstruct details, while also decomposing albedo, normal, and shading components [4].Authors propose UV texture map compression using R-RD optimization. Method updates texture map iteratively based on joint cost of bitrate and rendering distortion [5]. Authors propose a texture-aware local adaptive watermarking algorithm to maximize watermark robustness and imperceptibility by embedding in textured regions with higher visual quality than in smooth regions, using texture value to identify textured regions [6]. Authors introduced an interactive image segmentation technique that adapts segmentation parameters to each image, eliminating the need for offline parameter tuning or training. They formulated the segmentation problem as a conditional random field inference, with weights for color, texture, and smoothing [17]. The challenge of extracting meaningful structures on textured surfaces, whether regular, near-regular, or irregular, is of practical importance. A new approach introduces inherent and relative total variation measures to distinguish between visual forms and efficiently extract main structures. This method allows for manipulation, rendering, and reuse of "structure with texture" images traditionally hard to edit. It does not require prior texture information and may mistake some structures for texture if visually similar in scales [7].

The purpose of structure extraction is to break down an image into its main structures and textures. Researchers introduced a new method with two key steps: using a pre-smoothing filter to reduce high-frequency components related to texture information, and applying an anisotropic diffusion algorithm using a second neighbour derivative (SND) operator. They found that the SND operator is more effective for tasks like texture smoothing. The study also explored factors like pre-smoothing filter selection, iteration number, and scale parameter in the diffusion algorithm. Experiments were conducted to compare this method's performance in various image editing applications against other state-of-the-art algorithms [8].

A filtering-based method for image decomposition was presented, smoothing image gradients to filter out textures with an adaptive approach. A new interval gradient operator was introduced for this purpose. The method includes a gradient-guided algorithm for high-quality image filtering, avoiding gradient reversal and preserving sharp features. This method is suitable for accurate image structure-texture decomposition in various applications [9].

The proposed method aims to improve structure-preserving image and texture filtering performance by addressing the challenges of handling complex images with multiple scales of features. Unlike conventional filters, this approach focuses on adapting kernel scales for better balance between removing unimportant details and preserving important features. By using patch-based statistics, the method identifies textures from structures and determines an optimal per-pixel smoothing scale. It demonstrates improved filtering performance in protecting geometric structures like edges and corners while maintaining sharpness even with significant smoothing [10]. By adapting a windowed inherent variation to distinguish between textures and structures, the method successfully detects structure edges. The proposed filter has been demonstrated in various applications including seam carving, detail enhancement, and artistic rendering. Experimental results show the effectiveness of this method, comparing favourably to previous studies. Overall, structure-preserving filtering is essential in image processing, and this proposed algorithm offers a simple, fast, and effective solution [11].A new method was introduced to improve structure-preserving image and texture filtering, overcoming challenges with conventional edge-aware filters in handling complex images with multiple scale features. This approach focuses on adaptive kernel scales, identifying texture and optimal per-pixel smoothing scale through patch-based statistics. It may not be ideal for certain textures requiring explicit analysis or prior knowledge due to its reliance on texture oscillation properties. Future research directions could include accelerating the implementation and extending it to video processing [12].Bilateral texture filter enhances original bilateral filter by analysing texture features and preserving main image structures [13].Demosaicking and denoising in digital imaging are crucial yet challenging tasks, requiring inferring three color values from a single noisy measurement. Traditional methods use hand-crafted filters or priors but often have visual artifacts in difficult cases. A new data-driven approach using deep neural networks trained on a large image dataset has shown superior performance. By identifying challenging patches and mining community photographs, this approach outperforms existing techniques on both noisy and noise-free data, while being significantly faster [14].Image smoothing is crucial in computer vision and graphics. A new unsupervised learning framework uses CNNs to learn from data for flexible and high-quality smoothing effects. It includes edge-preserving regularizer and spatially-adaptive Lp flattening criterion for better results. Various image smoothing solutions for applications like abstraction, sketching, and enhancement are implemented, with results comparable to or better than previous methods [15].Image smoothing is a fundamental task in computer vision, that attempts to retain salient structures and remove insignificant textures. Here they aim to address the fundamental shortcomings of existing image smoothing methods, which cannot properly distinguish textures and structures with similar low-level appearance. While deep learning approaches have started to explore structure preservation through image smoothing, existing work does not yet properly address textures. To this end, they generated a large dataset by blending natural textures with clean structure-only images, and use this to build a texture prediction network (TPN) that predicts the location and magnitude of textures. They combined the TPN with a semantic structure prediction network (SPN) so that the final texture and structure aware filtering network (TSAFN) is able to identify the textures to remove (“textureawareness”) and the structures to preserve (“structure-awareness”). The proposed model is easy to understand and implement, and shows good performance on real images in the wild as well as our generated dataset [16].The automatic image segmentation problem is addressed using a region merging style with an initially over-segmented image. Homogeneous color regions are detected and merged iteratively according to a statistical test. The algorithm addresses merging order and stopping criterion with a novel predicate based on SPRT and maximum likelihood. The merging follows dynamic programming principles, forming image segmentation as an inference problem. The produced segmentation meets global properties, and a faster algorithm accelerates the region merging process by maintaining a nearest neighbourgraph [17]. The authors addressed the automatic image segmentation problem using a region merging approach. They proposed an algorithm that iteratively merges homogeneous color regions in an over-segmented image based on a statistical test. The algorithm addresses issues of merging order and stopping criteria using a novel predicate defined by SPRT and maximum likelihood. The merging order follows dynamic programming principles, and the final segmentation is based on observed image data. The algorithm also satisfies certain global properties and includes a faster iteration process with a nearest neighbourgraph [18]. They introduced new unsupervised region merging methods within a statistical framework to explain images at various levels. These methods feature general, non-parametric region models without color or texture assumptions, and employ innovative merging criteria based on statistical measures. Scale consistency is maintained through size regularization terms and unique merging orders [19]. Component-trees create a data structure based on binary components in gray-level images. An interactive segmentation approach using component-trees extracts a subset to generate a binary object matching a selected target. Advantages include precise segmentation without false contours, requiring only one image marker, and fast computation for real-time results on standard image sizes. No background marker is needed, distinguishing it from other methods [20].

A. Research Objectives:

To construct a deep learning model capable of learning and adapting image features for effective smoothening.

To incorporate interactive segmentation techniques to involve user input, allowing for personalized control over the smoothening process.
To assess the performance of the proposed method through rigorous experimentation and comparison with existing techniques.

b.Significance of the Study:

The proposed smoothening technique holds significant promise for applications across various domains. From medical imaging, where clarity and precision are paramount, to computer vision and photography, where visual aesthetics are crucial, the ability to enhance images while preserving essential details can have a transformative impact.
As we delve into the details of our methodology and present our experimental findings, this research aims to contribute to the evolving landscape of image processing, offering an innovative solution to the persistent challenge of image smoothening.

c. Literature Review

S.No.	Title	Authors	Source	Date
[1]	**Analyzing Satellite Images By Apply Deep Learning Instance Segmentation of Agricultural Fields** *Abstract: This novel research focuses on multi-exposure satellite images of agricultural fields using image analysis and deep learning techniques. The development of image edge smoothening .*	Atheer Joudah Mounir; Souheyl Mallat; M. Zrigui;	Periodicals of Engineering and Natural Sciences (PEN)	2021
[2]	**Interactive Medical Image Segmentation Using Deep Learning With Image-Specific Fine Tuning** *Abstract: Convolutional neural networks (CNNs) have achieved state-of-the-art performance for automatic medical image segmentation. However, they have not demonstrated sufficiently accurately.*	GUOTAI WANG et. al.	IEEE transactions on medical imaging	2018
[3]	**Deep Extreme Cut: From Extreme Points to Object**	KEVIS-KOKITSI MANINIS et. al.	cvpr	2018

S.No.	Title	Authors	Source	Date
	Segmentation **IF:6** *Highlight: This paper explores the use of extreme points in an object (left-most, right-most, top, bottom pixels) as input to obtain precise object segmentation for images and videos.*			
[4]	**DeepIGeoS: A Deep Interactive Geodesic Framework for Medical Image Segmentation** **IF:6** *Abstract: Accurate medical image segmentation is essential for diagnosis, surgical planning and many other applications.*	GUOTAI WANG et. al.	IEEE transactions on pattern analysis and machine ...	2018
[5]	**DeepIGeoS: A Deep Interactive Geodesic Framework For Medical Image Segmentation** **IF:6** *Highlight: We propose a deep learning-based interactive segmentation method to improve the results obtained by an automatic CNN and to reduce user interactions during refinement for higher accuracy.*	GUOTAI WANG et. al.	arxiv-cs.CV	2017
[6]	MIDeepSeg: Minimally Interactive Segmentation of Unseen Objects from Medical Images Using Deep Learning Abstract: Segmentation of organs or lesions from medical images plays an	XIANGDE LUO et. al.	Medical image analysis	2021

S.No.	Title	Authors	Source	Date
	essential role in many clinical applications such as diagnosis and treatment planning.			
[7]	Robust Object Categorization and Scene Classification Over Remote Sensing Images Via Features Fusion and Fully Convolutional Network Ibstract: The latest visionary technologies have made an evident impact on remote sensing scene classification. Scene classification is one of the most challenging yet important tasks in ...	Y. GHADI et. al.	Remote. Sens.	2022
[8]	Study on MRI Medical Image Segmentation Technology Based on CNN-CRF Model Abstract: Image segmentation is an important technique for segmenting images without overlapping each other and having their own features.	Naiqin Feng; Xiuqin Geng; Lijuan Qin;	IEEE Access	2020
[9]	DeepIGeoS-V2: Deep Interactive Segmentation of Multiple Organs from Head and Neck Images with Lightweight CNNs View Abstract: Accurate segmentation of organs-at-risks (OARs) from Computed Tomography (CT) image is a key step for efficient planning of radiation therapy for nasopharyngeal carcinoma (NPC) .	WENHUI LEI et. al.		2019

S.No.	Title	Authors	Source	Date
[10]	Brain Tumor Segmentation with Deep Learning Technique Abstract: The proposed work is based on Deep learning technique which is a deep neural network and probabilistic neural network to detect unwanted masses in the brain.	G MADHUPRIYA et. al.	2019 3rd International Conference on Trends in Electronics ...	2019
[11]	A Deep Framework for Bacterial Image Segmentation and Classification Abstract: Bacterial image segmentation and classification is an important problem because bacterial appearance can vary dramatically based on environmental conditions.	Dong Nie; Elizabeth A. Shank; Vladimir Jojic;	Proceedings of the 6th ACM Conference on Bioinformatics, ...	2015
[12]	Deep Learning in Precision Agriculture: Artificially Generated VNIR Images Segmentation for Early Postharvest Decay Prediction in Apples Abstract: Food quality control is an important task in the agricultural domain at the postharvest stage for avoiding food losses.	NIKITA STASENKO et. al.	Entropy (Basel, Switzerland)	2023
[13]	Segmentation of 3D Dental Images Using Deep Learning Related Papers Related Patents Related Grants Related Venues Related Experts View Highlight: This paper	Omar Boudraa;	arxiv-eess.IV	2022

S.No.	Title	Authors	Source	Date
	provides a multi-phase Deep Learning-based system that hybridizes various efficient methods in order to get the best 3D segmentation output.			
[14]	Region-Based Convolutional Neural Network-Based Spine Model Positioning of X-Ray Images Abstract: Idiopathic scoliosis accounts for over 80% of all cases of scoliosis but has an unclear pathogenic mechanism.	Le Zhang; Jiabao Zhang; Song Gao;	BioMed research international	2022
[15]	A Framework for Interactive Medical Image Segmentation Using Optimized Swarm Intelligence with Convolutional Neural Networks Abstract: Recent improvements in current technology have had a significant impact on a wide range of image processing applications, including medical imaging.	CHETNA KAUSHAL et. al.	Computational intelligence and neuroscience	2022

3. Methodology

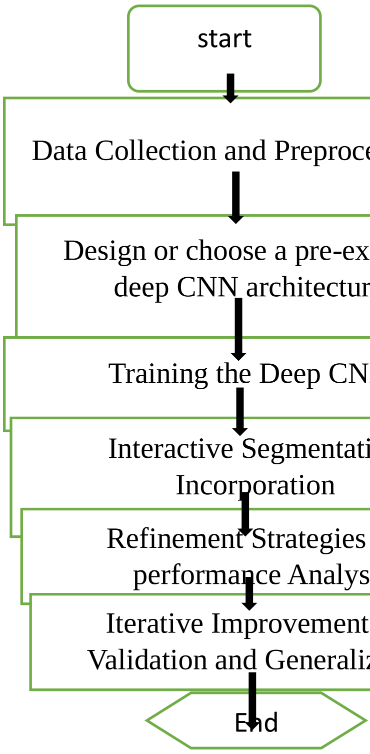

Figure 1: Flow chart ofImage Smoothening Techniques Using Deep CNN and Interactive Segmentation

Step1:Data Collection and Preprocessing:
Gather a diverse dataset of images relevant to your application (e.g., medical images, satellite images, etc.).Preprocess the images to ensure uniformity in terms of resolution, color space, and other relevant factors.

Step 2: Deep CNN Architecture:
Design or choose a pre-existing deep CNN architecture suitable for image smoothening tasks. This could be a convolutional autoencoder, U-Net, or another architecture known for feature extraction and image representation.

Step 3: Training the Deep CNN:

- Split your dataset into training, validation, and test sets.
- Train the deep CNN on the training set using appropriate loss functions (e.g., mean squared error for smoothening) and optimization techniques.
- Fine-tune the model using transfer learning if applicable.

Step 4:Interactive Segmentation Incorporation:
Integrate interactive segmentation techniques into the workflow. This could involve allowing user input to refine or modify segmented regions.
Implement algorithms or interfaces for user interaction with the segmentation results.

Step 5: Refinement Strategies:
Develop strategies for refining the segmentation results using interactive inputs.
Explore methods for adjusting segmentation boundaries, enhancing details, or smoothening specific regions based on user feedback.

Step 6: Performance Evaluation:
Assess the performance of the combined deep CNN and interactive segmentation model on the validation and test datasets.
Utilize relevant metrics (e.g., Mean Squared Error, Intersection over Union) to measure the quality of smoothening and segmentation.

Step 7:Iterative Improvement:

- Analyze the results and user feedback to identify areas for improvement.

- Iteratively refine the model and update the methodology based on the observed shortcomings.

Step 8: Validation and Generalization:

Validate the performance of the model on new and unseen datasets to ensure generalization.

Consider the robustness of the model across different types of images and applications.

4.Result and Discussion

```
!git clone https://github.com/OSSpk/Gradient-Smoothness-Structural_Similarity-Image_Histogram

import cv2
from matplotlib import pyplot as plt

# You can change the image name here
img = cv2.imread('/content/Gradient-Smoothness-Structural_Similarity-Image_Histogram/images/v1.jpg', 0)

laplacian = cv2.Laplacian(img, cv2.CV_64F)
plt.subplot(1, 2, 1), plt.imshow(img, cmap=plt.cm.gray)
plt.title('Original'), plt.xticks([]), plt.yticks([])
plt.subplot(1, 2, 2), plt.imshow(laplacian, cmap=plt.cm.gray)
plt.title('Gradient'), plt.xticks([]), plt.yticks([])

plt.show()
```

output

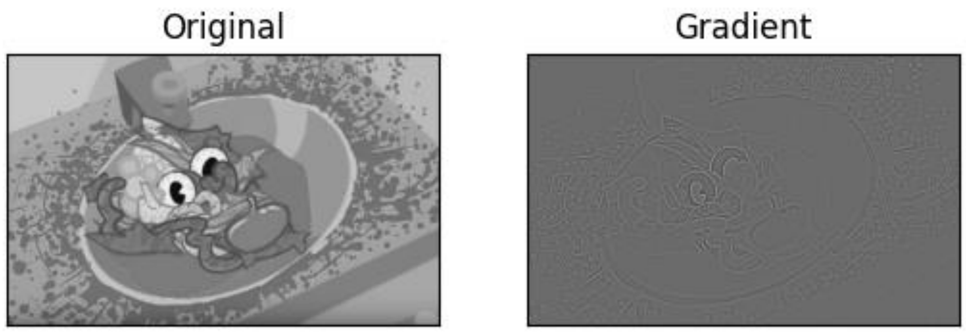

Figure 2: original and Gradient Image

```
import cv2
import matplotlib.pyplot as plt  # import pyplot as plt
import numpy as np

plt.style.use("seaborn-whitegrid")

# you can change image name here
img = cv2.imread('/content/Gradient-Smoothness-Structural_Similarity-Image_Histogram/images/v1.jpg')

color = ('b', 'g', 'r')

hists = []
for i, col in enumerate(color):
  histr = cv2.calcHist([img], [i], None, [256], [0, 256])
  plt.plot(histr, color=col)
  plt.xlim([0, 256])

plt.xlabel("Intensity Value", fontsize=12)
plt.ylabel("Count", fontsize=12)
plt.xticks(fontsize=12)
plt.title('Image Histogram')
plt.yticks(fontsize=12)
plt.show()
```

output

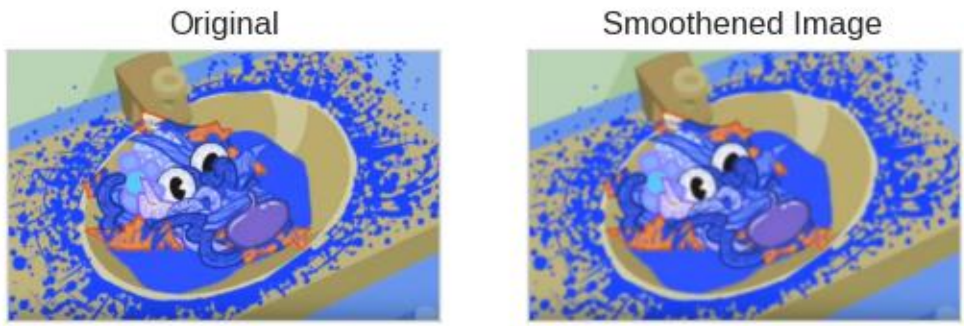

Figure3: original and smoothened Image

```
import cv2
import matplotlib.pyplot as plt  # import pyplot as
plt
import numpy as np

plt.style.use("seaborn-whitegrid")

# you can change image name here
img = cv2.imread('/content/Gradient-Smoothness-
Structural_Similarity-
Image_Histogram/images/v1.jpg')

color = ('b', 'g', 'r')

hists = []
for i, col in enumerate(color):
  histr = cv2.calcHist([img], [i], None, [256], [0, 256
])
  plt.plot(histr, color=col)
  plt.xlim([0, 256])

plt.xlabel("Intensity Value", fontsize=12)
plt.ylabel("Count", fontsize=12)
plt.xticks(fontsize=12)
plt.title('Image Histogram')
plt.yticks(fontsize=12)
plt.show()
output
```

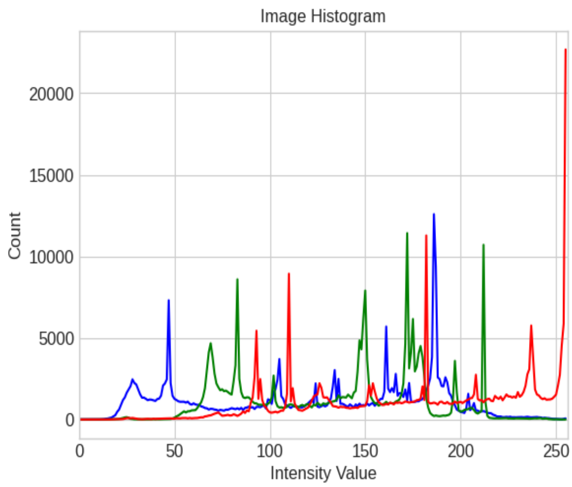

Figure 4:Image Histogram with intensity Value and Count

```
import cv2
import numpy as np
from matplotlib import pyplot as plt

# you can change the image name here
img = cv2.imread('/content/Gradient-Smoothness-
Structural_Similarity-
Image_Histogram/images/v1.jpg')

kernel = np.ones((5, 5), np.float32) / 25
dst = cv2.filter2D(img, -1, kernel)
plt.subplot(121), plt.imshow(img), plt.title('Original
')
plt.xticks([]), plt.yticks([])
plt.subplot(122), plt.imshow(dst), plt.title('Smooth
ened Image')
plt.xticks([]), plt.yticks([])
plt.show()
output
```

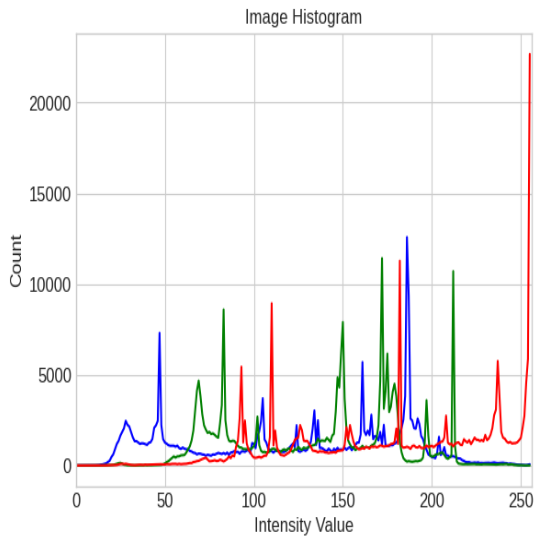

Figure 5:Image Histogram with intensity Value and Count

```
# import the necessary packages
import cv2
import numpy as np
from matplotlib import pyplot as plt
#from skimage.metrics import structural_similarity
 as ssim
#from skimage.measure import compare_ssim as s
sim
#from skimage import metrics metrics.structural_s
imilarity(grayA, grayB, full=True)
from skimage import measure
s = ssim(imageA, imageB)
#s = measure.compare_ssim(imageA, imageB)
def mse(imageA, imageB):
   # the 'Mean Squared Error' between the two im
ages is the
   # sum of the squared difference between the tw
o images;
   # NOTE: the two images must have the same di
mension
   err = np.sum((imageA.astype("float") -
 imageB.astype("float")) ** 2)
   err /= float(imageA.shape[0] * imageA.shape[1])

   # return the MSE, the lower the error, the more
"similar" the two images are
   return err


# you can change the image names here
# NOTE: first resize the images to equal sizes [using
 some online tool]
img1 = cv2.imread("/content/Gradient-
Smoothness-Structural_Similarity-
Image_Histogram/images/f1_equal.jpeg")
img2 = cv2.imread("/content/Gradient-
Smoothness-Structural_Similarity-
Image_Histogram/images/v1_equal.jpeg")

fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(1
0, 4),
                  sharex=True, sharey=True,
                  subplot_kw={'adjustable': 'box-
forced'})

mse_1 = mse(img1, img1)
ssim_1 = ssim(img1, img1, multichannel=True)

mse_2 = mse(img1, img2)
ssim_2 = ssim(img1, img2, multichannel=True)

label = 'MSE: {:.2f}, SSIM: {:.2f}'

axes[0].imshow(cv2.cvtColor(img1, cv2.COLOR_BG
R2RGB), vmin=0, vmax=1)
axes[0].set_xlabel(label.format(mse_1, ssim_1))
axes[0].set_title('Figure 1')

axes[1].imshow(cv2.cvtColor(img2, cv2.COLOR_BG
R2RGB), vmin=0, vmax=1)
axes[1].set_xlabel(label.format(mse_2, ssim_2))
axes[1].set_title('Figure 2')

plt.show()
```

output
Next steps:Explain error

- **The key finding which is Highlighted are :**
- **Scale-Aware Smoothening**: This refers to the ability of the smoothening technique to adapt to different scales in an image. This is crucial as objects in images can vary significantly in size, and a scale-aware approach ensures that smoothening is applied appropriately across different structures.
- **Structure-Aware Smoothening**: The method considers the inherent structures within an image, preserving important features while smoothing out unwanted noise. Preserving

structures is essential for maintaining the integrity and content of the image.

- **Deep CNNs**: These are powerful models for image processing tasks, capable of learning intricate features and patterns from data. Utilizing a deep CNN, such as U-Net, in the context of image segmentation enables the identification and isolation of specific regions in an image.
- **Interactive Segmentation:** Involving users in the segmentation process allows for customization and refinement. Users can provide input to guide the segmentation, making the process more adaptable to diverse images and user preferences.
- **Adaptive Filtering:** Adaptive filtering techniques dynamically adjust the filter characteristics based on the local properties of the image. This allows for more effective noise reduction and smoothening in varying image regions.
- **Watermarking Methodologies**: Watermarking is a technique used to embed information (watermark) into an image for purposes such as copyright protection. Integrating watermarking methodologies suggests an additional layer of security or information embedding within the smoothening process.
- **Denoising:** Denoising involves the removal of unwanted noise from an image. Innovative denoising procedures likely incorporate advanced algorithms or techniques to effectively reduce noise while preserving image details.
- The integration of scale-aware and structure-aware smoothening techniques ensures a versatile approach capable of handling diverse images.
- Deep CNNs and interactive segmentation contribute to accurate and user-guided segmentation, allowing for customized and real-time results.
- Joint adaptive filtering enhances smoothening by dynamically adjusting to the characteristics of different image regions, improving noise reduction.
- Watermarking methodologies introduce a layer of information embedding, potentially offering additional functionality or security in the smoothening process.
- Innovative denoising procedures likely contribute to the overall quality of the smoothened image by efficiently reducing noise without compromising important details.
- In conclusion, the combination of these techniques suggests a comprehensive and sophisticated approach to real-time image smoothening, emphasizing adaptability, user interaction, and advanced filtering methodologies.

5.Conclusion

In conclusion, image smoothening techniques using deep CNN and interactive segmentation offer powerful tools for enhancing and refining images. The combination of deep convolutional neural networks (CNN) and interactive segmentation provides a robust approach for achieving smooth and visually appealing results.Deep CNNs, such as U-Net architectures, excel in image segmentation tasks by learning hierarchical features and capturing complex patterns. These networks can effectively distinguish between different regions in an image, making them suitable for tasks like identifying boundaries and creating segmentation masks.Interactive segmentation adds an extra layer of user control to the image smoothening process. Users can actively participate in defining regions of interest or specifying areas for smoothening, allowing for more personalized and fine-tuned results. This interactive element enhances the flexibility and adaptability of the smoothening process to various images and user preferences.Implementing such techniques in Python involves loading pre-trained models, preprocessing images, predicting segmentation masks, and applying smoothening algorithms. Depending on the specific requirements, integrating graphical user interfaces (GUIs) may enhance the user experience, allowing users to interactively guide the segmentation and smoothening process.Overall, image smoothening techniques using deep CNN and interactive segmentation showcase the synergy between advanced deep learning models and user-driven interactions, offering a powerful approach for improving image quality and aesthetics.

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