Enhancing Image Resizing: The Development and Evaluation of SeamCarver, An Advanced Content-Aware Software Package

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Abstract

This paper presents "SeamCarver," an advanced software package that enhances the traditional seam carving technique for image resizing. SeamCarver introduces several innovative methods to overcome the limitations of standard seam carving, particularly in handling images with complex features and preserving structural integrity. Key enhancements include the integration of bicubic interpolation for improved image enlargement, the application of the LC (Loyalty-Clarity) algorithm to maintain principal image characteristics, and the use of Canny edge detection to refine image outlines. Additionally, the software incorporates the Hough transformation for effective line detection and augmentation, coupled with an absolute energy function to optimize seam carving performance. A dual energy function, offering an alternative to the forward energy approach, further refines the process. To assess the efficacy of these methods, we conducted image classification experiments using Convolutional Neural Networks (CNN) on the CIFAR-10 dataset, demonstrating significant improvements in image quality and resizing accuracy. Our findings reveal that while bicubic interpolation can introduce shadow artifacts in certain scenarios, the combined use of Hough Transformation and seam carving excels in preserving linear features. We also propose the integration of the GrabCut algorithm with seam carving as a future direction, aiming to achieve more content-aware resizing, particularly vital in maintaining the integrity of key image regions. SeamCarver thus stands out as a substantial enhancement over traditional seam carving methods, offering robust, versatile, and quality-focused image resizing capabilities.

I. Introduction

In this paper, we present "SeamCarver," a sophisticated software package that advances the field of image resizing through an enhanced implementation of seam carving, a technique originally introduced by Avidan and Shamir. Seam carving is distinguished by its content-aware methodology, which dynamically adjusts the dimensions of images by meticulously removing seams—paths of low-energy pixels—either vertically or horizontally. This process uniquely preserves the integrity of the image's key features, a significant improvement over traditional resizing methods.

Despite its innovative approach, the original seam carving technique had notable limitations, including simplistic energy map creation and basic energy dynamic programming. These limitations often resulted in inadequate preservation of important image characteristics. Addressing these issues, our software package SeamCarver incorporates several key enhancements. We have integrated bicubic interpolation for superior image enlargement and implemented the LC algorithm to more effectively preserve main image characteristics. Furthermore, our approach includes the utilization of the Cany line for refined image outlines and the application of the Hough transformation to identify and enhance significant lines within images. A novel addition to our software is the introduction of an absolute energy function, designed to optimize the performance of seam carving.

Additionally, SeamCarver features a dual energy function, developed as an alternative version of the forward energy concept, further refining the seam carving process. To demonstrate the effectiveness of these enhancements, we have conducted comprehensive image classification experiments using Convolutional Neural Networks (CNN), showcasing significant improvements in performance.

This paper aims to not only introduce the various functionalities of SeamCarver but also to provide a thorough analysis of its performance. By detailing the advancements our software makes over traditional seam carving methods, we highlight its potential applications in both photography and computer vision, offering a substantial contribution to the field of digital image processing.

II. Functionality

This section outlines the key functionalities of the SeamCarver software package, highlighting the advanced methods integrated to enhance the original seam carving model. Each functionality contributes to the overall effectiveness and efficiency of the software, ensuring high-quality image resizing while preserving essential image characteristics.

- **Bicubic Interpolation for Image Enlargement:** SeamCarver employs bicubic interpolation to ensure smooth and high-quality image enlargement, a critical aspect for maintaining visual fidelity.
- **Integration of the LC Algorithm:** The software incorporates the LC (Loyalty-Clarity) algorithm to safeguard the main visual elements during the resizing process, ensuring that key features of the image are preserved.
- **Enhancement via Canny Edge Detection:** Utilizing the Canny edge detection algorithm, SeamCarver effectively enhances image outlines, contributing to clearer and more defined images.
- **Hough Transformation for Line Detection:** The Hough transformation is adeptly applied to detect and accentuate the most significant lines in images, thereby augmenting structural integrity.
- **Absolute Energy Function for Optimized Seam Carving:** An absolute energy function is implemented to refine the seam carving process, optimizing the selection and removal of seams for better resizing results.
- **Dual Energy Function Implementation:** This feature introduces an alternative to the traditional forward energy approach, adding a layer of sophistication to the seam carving algorithm.
- **Performance Evaluation through CNN:** The efficacy of SeamCarver's enhancements is quantitatively assessed using image classification experiments based on Convolutional Neural Networks (CNN), underscoring the software's advanced capabilities[1].

III. Bicubic Interpolation for Image Enlargement

In enhancing the image resizing capabilities of SeamCarver, we have integrated a bicubic interpolation method, specifically tailored for image enlargement. This method leverages the bicubic policy to smooth pixel values, significantly enhancing the visual quality of enlarged images.

[1] Detailed evaluations are presented in the subsequent sections.

i. Algorithmic Approach

The bicubic interpolation algorithm is rooted in the principle of utilizing the grey values of a 4x4 pixel grid surrounding the target pixel. This comprehensive approach not only considers the grey values of the four directly adjacent pixels but also accounts for the rate of change in grey value between these adjacent points. The algorithm effectively transforms discrete data into continuous functions through a process akin to convolution.

ii. Computational Process

The essence of this method lies in determining the floating-point pixel coordinate position (decimal representation) of the target pixel within the original image. This is achieved by considering the scaling relationship and calculating the weighted sum of the surrounding 16 pixels' values. The interpolation weights are determined based on the relative distance to the target pixel. The corresponding coordinates in the original image, denoted as B(x,y), are computed using the following formulas:

$$w(x) = \begin{cases} (a+2)|x|^3 - (a+3)|x|^2 + 1, & \text{if } x<=1 \\ a|x|^3 + 5a|x|^2 + 8a|x| - 4a, & \text{if } 1<x<2 \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

$$B(X,Y) = \sum_{i=0}^{3}\sum_{j=0}^{3} a_{ij} \cdot w(x - X_i) \cdot w(y - Y_j) \tag{2}$$

The interpolation for a pixel point (x, y), which can be floating-point numbers, involves taking the 4x4 neighborhood points (x_i, y_j), where $i, j = 0, 1, 2, 3$, and performing the calculation as per the following equation:

$$f(x,y) = \sum_{i=0}^{3}\sum_{j=0}^{3} f(x_i, y_j) \cdot w(x - x_i) \cdot w(y - y_j) \tag{3}$$

iii. Practical Application and Examples

Subsequent sections will provide practical examples illustrating the efficacy of this bicubic interpolation method when applied to image enlargement, showcasing the significant improvements in image quality achieved through this approach.

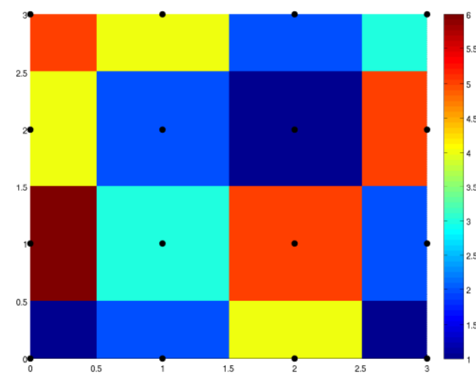


Figure 1: *original image*

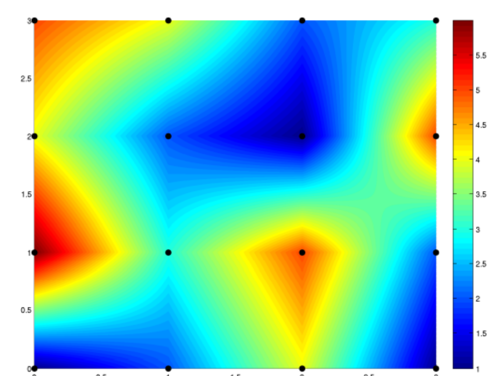


Figure 2: *bilinear interpolation*

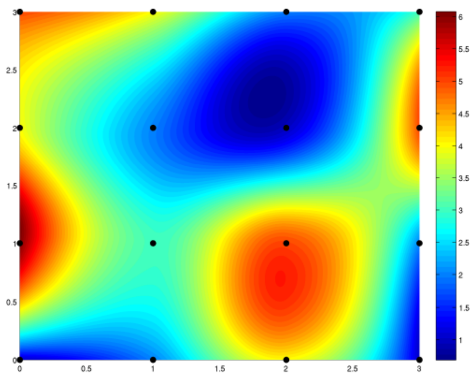


Figure 3: *bicubic interpolation*

IV. LC (Loyalty-Clarity) Policy

The LC (Loyalty-Clarity) Policy is a sophisticated algorithm employed in SeamCarver to enhance the main characteristics of an image. This method is pivotal in emphasizing the essential features of an image while performing resizing operations. It functions by calculating the global contrast of each pixel relative to the entire image, offering a nuanced approach to image enhancement.

i. Global Contrast Calculation

The global contrast of a pixel is determined by summing the distances in color space between the pixel in question and all other pixels within the image. This distance serves as a significant value for the pixel, quantifying its contrast in relation to the entire image. The mathematical representation of this calculation for a grayscale image is as follows:

$$SalS(I_k) = \sum_{\forall I_i \in I} \|I_k - I_i\| \quad (4)$$

Here, I_k represents the intensity value of the pixel being analyzed, and I_i encompasses all other pixels in the image.

ii. Frequency-Based Refinement

In practical application, this calculation can be further refined considering the frequency distribution of intensity values in the image. Given an image where $I_k = a_m$ for a specific pixel and f_n represents the frequency of each unique intensity value a_n, the global contrast calculation can be expressed as:

$$SalS(I_k) = \sum_{n=0}^{255} f_n \|a_m - a_n\| \quad (5)$$

In this formulation, the sum is taken over all possible intensity values (ranging from 0 to 255 in a grayscale image), weighted by their frequency in the image. This approach ensures a more efficient and representative calculation of the global contrast, thereby enabling the LC Policy to more accurately enhance the salient features of the image.

iii. Application in Image Resizing

The integration of the LC Policy in SeamCarver allows for a more content-aware resizing process. By calculating and considering the global contrast of each pixel, the software can make more informed decisions about which areas of the image to preserve and which to modify, ensuring that key features and contrasts within the image are maintained even after resizing.

Figure 4: *the outlier detected by LC algorithm*

V. Canny Line Detection

In the SeamCarver software, the Canny Line Detection algorithm is employed to perform line augmentation, significantly enhancing the edge definition within images. This method is crucial for identifying and emphasizing the prominent structural features of an image, which is essential in content-aware image resizing.

i. Algorithm Overview

The Canny Edge Detection algorithm is renowned for its efficiency in detecting a wide range of edges in images. It operates by identifying the intensity gradients of the image, thereby highlighting the most prominent edges.

ii. Gaussian Filter Application

The first step in the Canny Edge Detection process involves smoothing the image using a Gaussian filter. This is essential for reducing noise and minimizing the likelihood of detecting false edges. The Gaussian filter is mathematically represented as:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{6}$$

Here, σ represents the standard deviation of the Gaussian filter, and (x, y) are the coordinates of the pixel in the image.

iii. Gradient Calculation

Post-Gaussian filtering, the algorithm computes the gradient of the image using the Sobel operator, which calculates the first derivative in both horizontal (x) and vertical (y) directions. The gradient magnitude and direction at each pixel (i, j) are given by:

$$G(i,j) = \sqrt{G_x(i,j)^2 + G_y(i,j)^2} \tag{7}$$

$$\theta(i,j) = \arctan\left(\frac{G_y(i,j)}{G_x(i,j)}\right) \tag{8}$$

Where $G_x(i, j)$ and $G_y(i, j)$ are the horizontal and vertical derivatives of the Gaussian blurred image, respectively.

iv. Edge Enhancement

The Canny algorithm further refines the detected edges through non-maximum suppression and hysteresis thresholding, ensuring that only the most significant edges are preserved. This process effectively augments the lines within the image, making them more pronounced and clear.

v. Significance in Image Resizing

Incorporating the Canny Line Detection algorithm into SeamCarver allows for more precise edge and line preservation during the image resizing process. By emphasizing critical edges, the algorithm ensures that the resized images retain their structural integrity and visual clarity, a key aspect of content-aware resizing.

Figure 5: *original picture*

Figure 6: *the edges detected by Canny detector*

VI. Hough Transformation for Line Detection

The SeamCarver software employs the Hough Transformation for enhanced line detection, crucial in maintaining image structure during resizing. This method transforms image data into a parametric space, facilitating the detection of linear patterns.

i. Algorithm Overview

The Hough Transformation algorithm translates points from the image domain to the Hough space, where collinear points in the image domain converge to peaks, indicating the presence of lines.

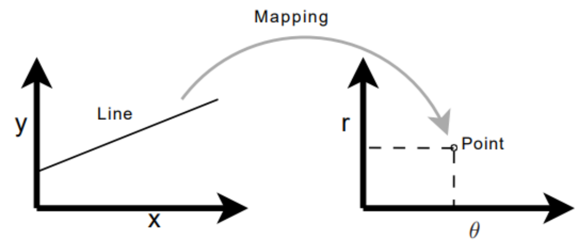


Figure 7: *mapping from space to points*

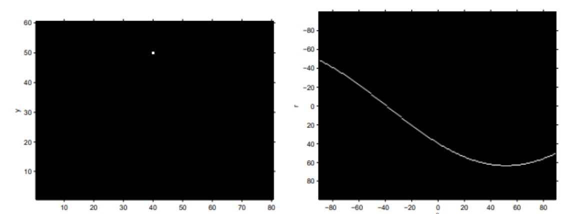
ii. Algorithmic Steps

The implementation of the Hough Transformation for line detection in SeamCarver is summarized in the following algorithm:

Algorithm 1 Hough Transformation for Line Detection

Require: *Image*: input digital image;
Ensure: Lines detected in the image.

```
Apply edge detection (e.g., Canny edge detector).
Initialize Hough space and accumulator.
for each edge pixel (x, y) do
    for each angle θ do
        Compute r = x cos(θ) + y sin(θ).
        Increment accumulator at (r, θ).
    end for
end for
Detect peaks in accumulator as lines.
Convert infinite lines to finite lines.
```



(a) Point p_0.   (b) All possible lines through p_0 represented in the Hough space.

Figure 8: *mapping from points to space*

Figure 9: *original picture*

iii. Impact on Image Resizing

The integration of Hough Transformation in SeamCarver significantly improves the software's ability to identify and preserve key linear features during image resizing, ensuring the retention of structural details and overall image quality.

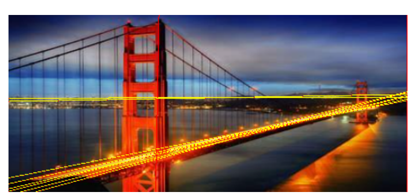


Figure 10: *the lines detected by hough transformation with the background*

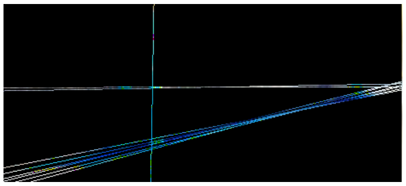


Figure 11: *the lines detected by hough transformation*

VII. Absolute Energy Equation

In SeamCarver, the Absolute Energy Equation is implemented to address the limitations in dynamic programming performance of the original seam carving method, particularly for images with high detail concentration. This approach significantly enhances the software's capability to handle complex images by considering the energy gradient along the seams.

i. Conceptual Overview

The Absolute Energy Equation introduces an energy gradient cost functional into the dynamic programming process. This functional is specifically designed to avoid seams traversing areas with local extrema in the image. The rationale behind this approach is that local extrema, even if minor, imply a certain energy gradient necessary to be classified as a minimum or maximum. By incorporating this gradient, the software is more adept at highlighting even subtle extrema, adopting a conservative strategy in determining which parts of the image to remove.

ii. Algorithmic Formulation

The cumulative energy matrix update is formulated as follows, integrating both backward and forward energy functionals with the additional energy gradient cost:

$$s = \arg\min_{s}\{E(s)\} = \arg\min_{s}\{\sum_{i=1}^{n} e(I(s))\} \tag{9}$$

Where $e(I)$ represents the energy of the image I, calculated as the sum of the absolute gradients in both x and y directions:

$$e(I) = \left|\frac{\partial I}{\partial x}\right| + \left|\frac{\partial I}{\partial y}\right| \tag{10}$$

The cost components C_L, C_R, and C_U are defined for each pixel (i, j) as follows:

$$\begin{cases} C_L(i,j) = |I(i,j+1) - I(i,j-1)| \\ C_R(i,j) = |I(i,j+1) - I(i,j-1)| \\ C_U(i,j) = |I(i,j+1) - I(i,j-1)| \end{cases} \tag{11}$$

iii. Comparative Energy Functions

The original energy function is updated using the minimum of the cost components:

$$e(i,j) = e(i,j) + \min \left\{ \begin{array}{r} C_L(i,j) + e(i-1,j-1) \\ C_R(i,j) + e(i-1,j+1) \\ C_U(i,j) + e(i-1,j) \end{array} \right\} \tag{12}$$

In contrast, the Absolute Energy function incorporates the absolute energy gradient:

$$\begin{aligned} e(i,j) = e(i,j) + |e(i,j+1) - e(i,j)| + \\ |e(i+1,j) - e(i,j)| + \\ min \left\{ \begin{array}{r} C_L(i,j) + e(i-1,j-1) \\ C_R(i,j) + e(i-1,j+1) \\ C_U(i,j) + e(i-1,j) \end{array} \right\} \end{aligned} \tag{13}$$

iv. Impact on Image Processing

The Absolute Energy Equation in SeamCarver offers a refined approach to determining the optimal seams for removal, particularly in images with significant detail. By accounting for the energy gradient, the software is better equipped to maintain the integrity of critical image areas while efficiently resizing the image.

VIII. Dual Gradient Energy Equation

In SeamCarver, we advance the original seam carving method by employing the Dual Gradient Energy Equation. This approach, designed to enhance edge detection capabilities, utilizes numerical differentiation to achieve a more refined edge filter compared to the baseline Scharr operator.

i. Taylor Expansion and Numerical Differentiation

The foundation of the Dual Gradient Energy Equation lies in the Taylor series expansion and its application in numerical differentiation. The function $f(x)$ and its translations are expressed as:

$$f(x+\triangle x) = f(x) + \triangle x f'(x) + \triangle x^2 \frac{f''(x)}{2!} + \triangle x^3 \frac{f'''(\xi_1)}{3!} + \triangle x^4 \frac{f^{(4)}(x)}{4!} + \triangle x^5 \frac{f^{(5)}(\xi_1)}{5!}, \quad \xi_1 \in (x, x+\triangle x) \tag{14}$$

$$f(x-\triangle x) = f(x) - \triangle x f'(x) + \triangle x^2 \frac{f''(x)}{2!} - \triangle x^3 \frac{f'''(\xi_2)}{3!} + \triangle x^4 \frac{f^{(4)}(x)}{4!} - \triangle x^5 \frac{f^{(5)}(\xi_2)}{5!}, \quad \xi_2 \in (x, x+\triangle x) \tag{15}$$

From these expansions, we derive the $O(\Delta x^2)$ forward and backward difference approximations for the first derivative $f'(x)$.

ii. Forward Difference Approximation

Considering a uniform step size $\Delta x = \delta = 1$, we apply the forward difference approximation to compute the partial derivatives $f_x(x,y)$ and $f_y(x,y)$:

$$f_x(x,y) \approx \frac{-3f(x,y) + 4f(x+\delta,y) - f(x+2\delta,y)}{2} \tag{16}$$

$$f_y(x,y) \approx \frac{-3f(x,y) + 4f(x,y+\delta) - f(x,y+2\delta)}{2} \tag{17}$$

iii. Energy Calculation

For energy calculation, we consider the squared sum of the gradient energies for each RGB channel in both directions:

$$\Delta_x^2(x,y) = R_x(x,y)^2 + G_x(x,y)^2 + B_x(x,y)^2 \tag{18}$$

$$\Delta_y^2(x,y) = R_y(x,y)^2 + G_y(x,y)^2 + B_y(x,y)^2 \tag{19}$$

Finally, the total energy of a pixel is calculated as the square root of the sum of these squared gradients:

$$energy = \sqrt{\Delta_x^2(x,y) + \Delta_y^2(x,y)} \tag{20}$$

iv. Application in SeamCarving

This Dual Gradient Energy Equation enables SeamCarver to more accurately detect edges and gradients within images. By capturing finer details and nuances in the image structure, this method significantly enhances the seam carving process, especially in images with complex textures and edges.

IX. Result Evaluation

In order to assess the efficacy of the various image resizing methods implemented in SeamCarver, we conducted an experiment using Convolutional Neural Networks (CNN) for image classification. This experiment aimed to compare the performance of different resizing techniques based on their impact on image classification accuracy.

i. Experimental Setup

The experiment involved resizing images using different methods implemented in SeamCarver and then evaluating the impact of these resizing techniques on image classification. The CIFAR-10 dataset, a well-known benchmark in image classification, was used for this purpose.

ii. Methodology

The workflow of the experiment is as follows:

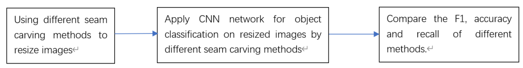


Figure 12: *Workflow of the experiment*

The CNN model was trained on the original CIFAR-10 images, and then the same network was used to classify images that had been resized using different methods in SeamCarver. This approach allowed us to assess how well each resizing method preserved the key features necessary for accurate image classification.

iii. Results and Discussion

The results of the experiment, including error rates and accuracy metrics for each sub-experiment, are provided at the end of the paper. Additionally, the implementation code for the evaluation can be found in the evaluation module of the code section.

Figure 13: *Error and accuracy of a sub-experiment (Further results can be found in the code section)*

Illustrative examples of images processed by different methods are shown below, highlighting the visual differences in the resized images:

Figure 14: *Image processed by the Bicubic Method*

Figure 15: *Image processed by the Absolute Energy Method*

Figure 16: *Image processed by the Canny Edge Detection Method*

Figure 17: *Image processed by the Dual Gradient Energy Method*

Figure 18: *Image processed by the Hough Transformation Method*

Figure 19: *Image processed by the LC Method*

iv. Conclusion

This experiment provides valuable insights into the effectiveness of different image resizing methods in maintaining the integrity of key features for image classification. The findings highlight the importance of choosing the right resizing technique for applications where image recognition accuracy is critical.

X. Discussion

This section provides a detailed analysis of the results obtained from various image resizing methods implemented in SeamCarver, highlighting their strengths, limitations, and potential areas for future development.

i. Limitations of Bicubic Interpolation

The bicubic interpolation method, a standard approach in image resizing, exhibits a noticeable limitation in certain scenarios. A shadowing effect is observed at the upper and right edges of the image, particularly in areas where the pixel intensity is lower compared to the rest of the image. This issue could be attributed to the nature of bicubic interpolation, which can over-smooth edges leading to a loss of detail and contrast, especially in regions with sharp intensity gradients.

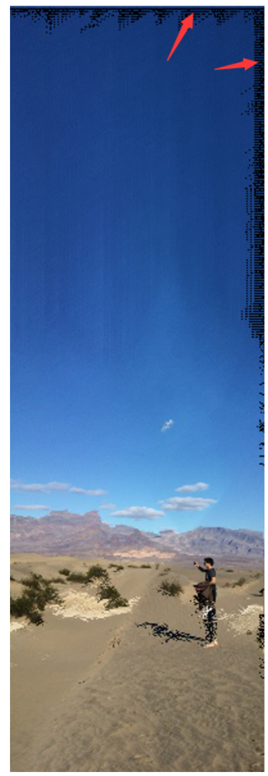


Figure 20: *Shadowing effect observed in the Bicubic Interpolation method*

Further refinement of the bicubic interpolation algorithm, possibly through adaptive parameter tuning or hybrid approaches, could mitigate this issue.

ii. Superior Performance of Hough Transformation Combined with Seam Carving

The integration of the Hough Transformation with the seam carving method has yielded impressive results, particularly in images with prominent linear structures. This combination excels over the original seam carving method by effectively preserving the integrity and continuity of straight lines in the image. This improvement can be attributed to the Hough Transformation's ability to detect and enhance linear features, which are then seamlessly integrated into the seam carving process.

Figure 21: *Enhanced results using Hough Transformation and Seam Carving*

Figure 22: *Comparison with the original Seam Carving method*

iii. Exploring Future Directions: Integrating GrabCut with Seam Carving

To further advance the capabilities of SeamCarver, the integration of the GrabCut algorithm, a well-known technique for image segmentation, is proposed. This method, which segments an image into foreground and background components, could be leveraged to enhance the seam carving process. By accurately distinguishing between important and less important regions of an image, the GrabCut algorithm can guide the seam carving process, ensuring that critical areas are preserved while less significant parts are altered.

Algorithm 2 Proposed Integration of GrabCut with Seam Carving

Initialize:
Construct the image as a graph;
Define background T_B, set foreground $T_F = \emptyset$, and $T_U = \overline{T_B}$;
Initialize $\alpha_n = 0$ for $n \in T_B$ and $\alpha_n = 1$ for $n \in T_U$.
Iteration:
1. Update node labels: $k_n := \arg\min_{k_n} D_n(\alpha_n, k_n, \theta, z_n)$
2. Optimize parameters: $\underline{\theta} = \arg\min_{\underline{\theta}} U(\underline{\alpha}, \mathbf{k}, \underline{\theta}, z)$
3. Minimize energy: $\{\alpha_n : n \in T_U\} = \arg\min_{\mathbf{k}} \mathbf{E}(\underline{\alpha}, \mathbf{k}, \underline{\theta}, z)$
4. Repeat until convergence, identifying optimal seams for carving.

This integration promises to deliver a more content-aware approach to image resizing, particularly useful in scenarios where maintaining the integrity of key image regions is critical.

References

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[Johannes Kiess, 2014] Johannes Kiess. Seam Carving with Improved Edge Preservation study.

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[Michael Frankovich, 2011] Michael Frankovich. Enhanced Seam Carving via Integration of Energy Gradient Functionals

Table 1: *The evaluation result of different methods*
(Note: TES: test set, VS: validation set,TRS: train set
ORG: original seam carving method
DI: doublecubic interpolation
HT:Hough Transformation
AE: absolute gradient function
DG: dual gradient function).

Model		Size		Epoches	F1	Accuracy			Recall		
		X size	Y size			TES	VS	TRS	TES	VS	TRS
ORG	exp1	300	600	10	93.2%	93.2%	93.2%	91.1%	92.3%	93.3%	95.9%
	exp2	400	500	8	94.1%	93.4%	93.8%	92.9%	92.8%	95.7%	93.6%
	exp3	500	800	11	91.8%	91.4%	91.2%	93.1%	93.3%	92.2%	92.7%
DI	exp1	300	600	10	95.3%	93.6%	92.5%	93.1%	98.3%	93.3%	91.2%
	exp2	400	500	8	94.2%	93.5%	92.4%	92.3%	95.8%	97.2%	94.2%
	exp3	500	800	11	95.5%	94.4%	90.1%	92.3%	97.1%	92.3%	92.8%
LC	exp1	300	600	10	95.3%	93.1%	94.1%	90.6%	97.2%	93.6%	96.1%
	exp2	400	500	8	94.2%	94.3%	96.6%	92.3%	94.1%	96.6%	93.1%
	exp3	500	800	11	94.3%	94.4%	91.2%	93.1%	94.3%	92.7%	95.9%
Canny	exp1	300	600	10	97.2%	97.2%	94.2%	91.1%	97.3%	94.3%	96.2%
	exp2	400	500	8	95.7%	94.2%	97.5%	92.3%	97.2%	98.8%	93.7%
	exp3	500	800	11	93.8%	94.4%	91.8%	93.8%	93.3%	95.7%	93.9%
HT	exp1	300	600	10	96.6%	95.2%	94.3%	93.1%	97.9%	94.1%	96.4%
	exp2	400	500	8	94.1%	96.4%	98.0%	91.4%	92.2%	96.2%	92.3%
	exp3	500	800	11	94.8%	96.4%	91.8%	97.1%	93.2%	91.7%	92.6%
AE	exp1	300	600	10	95.2%	97.2%	93.2%	96.7%	93.3%	98.0%	91.5%
	exp2	400	500	8	96.4%	97.4%	96.8%	98.9%	95.8%	97.7%	94.2%
	exp3	500	800	11	96.3%	96.1%	93.2%	94.4%	96.5%	91.6%	95.2%
DG	exp1	300	600	10	95.6%	97.2%	94.2%	91.1%	92.3%	97.3%	96.8%
	exp2	400	500	8	93.2%	92.4%	96.8%	92.9%	95.8%	93.2%	95.2%
	exp3	500	800	11	94.7%	96.4%	92.2%	92.5%	93.1%	95.8%	92.3%