International Student Research Review
Volume 2 Issue 1 May 2025
DOI: https://doi.org/10.53378/isrr.165

Enhancement of seam carving algorithm for optimized content-aware image resizing application

[1]Eliza Joyce B. Lim, [2]Louweesiana M. Buscas, [3]Vivien A. Agustin & [4]Khatalyn E. Mata

Abstract

Seam carving is a popular method of resizing an image while maintaining important content by adding or removing seams. The key to this approach is the importance map, distinguishing seams of the least visual significance. Nevertheless, traditional approaches struggle to preserve local and global image characteristics, causing visible artifacts that can significantly diminish visual fidelity. This study presents a new importance map combining Bubble Entropy, a Euclidean distance saliency map, and Haar wavelets for edge detection. Bubble Entropy is excellent at finding regularity and structural continuity across pixel neighborhoods, tracing significant seams. The saliency map's perceptually uniform property enhances color variation assessment, improving the detection of salient regions and textures. Additionally, Haar wavelet transforms enhance edge detection by maintaining structural transitions while resizing. By calculating the combined importance map, the proposed approach settles at the optimal balance between local and global characteristics of an image. The proposed algorithm outperforms previous seam carving algorithms in terms of perceptual quality metrics: LPIPS, MSSIM, HyperIQA and TOPIQ with the RetargetMe dataset. Execution time was also significantly reduced using the Numba package. Experimental results show image content preservation while improving visual quality and presenting a stronger approach for content-aware image resizing.

Keywords: *seam carving, entropy, bubble entropy, saliency map, haar, wavelet filter*

Article History:

***Received**: March 15, 2025*
***Revised**: May 12, 2025*
***Accepted**: May 25, 2025*
***Published online**: May 31, 2025*

Suggested Citation:
Lim, E.J.B., Buscas, L.M., Agustin, V.A. & Mata, K.E. (2025). Enhancement of seam carving algorithm for optimized content-aware image resizing application. *International Student Research Review*, 2(1), 74-90. https://doi.org/10.53378/isrr.165

About the authors:
[1]Corresponding author. 4th Year Bachelor of Science in Computer Science Student at Pamantasan ng Lungsod ng Maynila. Email: elizalim036@gmail.com
[2]4th Year Bachelor of Science in Computer Science Student at Pamantasan ng Lungsod ng Maynila.
[3]Master in Information Technology and CISTM Professor at Pamantasan ng Lungsod ng Maynila.
[4]Doctor in Information Technology and CISTM Dean at Pamantasan ng Lungsod ng Maynila.

1. Introduction

Recent advancements in display technology have introduced a wide range of display sizes, demanding the adaptation of the same content to various dimensions and aspect ratios across different devices. Web pages account pixel dimensions or resolutions when displaying images. Most common screen resolutions for desktop screens range from 1024×768 to 1920×1080, mobile screens range from 360×640 to 414×896, and tablets range from 601×962 to 1280×800 (Polson, 2024). Traditional downscaling, which uniformly reduces all image elements, often makes small objects harder to recognize (Pal & Tripathi P., 2016). This lack of consideration can lead to key details being lost or distorted, emphasizing the need for more sophisticated image adjustment techniques that respect the integrity of the original content.

Seam Carving is a content-aware image resizing method that adapts images to new dimensions by intelligently carving out or inserting pixels in areas based on their significance. In contrast to conventional resizing methods like cropping and scaling, which are content-agnostic, seam carving maintains visual features such as the aspect ratio and the composition of objects, thereby preserving the intrinsic aesthetics of the image. A seam represents a path of low-energy pixels within the image and can be vertical or horizontal. A vertical seam traverses from the top to the bottom of the image, intersecting one pixel per row, whereas a horizontal seam spans from left to right, touching one pixel per column. Its optimality can be defined by the energy function, and the seams can either be removed to reduce image size or duplicated to expand them.

The key to seam carving is the generation of the importance map as a basis for carving out the least important seams. However, traditional seam carving algorithms suffer from the following drawbacks: (1) noticeable artifacts that degrade the resized image's visual quality due to the algorithm's importance map failing to capture global features of the image; and (2) time-consuming calculation of image's energy map, insertion and removal of optimal seams leads to the algorithm's low execution speed. This research directly addresses these limitations, aiming to refine the seam carving process. To achieve this, an implementation of a new importance map combining Bubble entropy, Euclidean distance saliency map, and Haar wavelets for edge detection are integral to highlight the images local and global information. Furthermore, to address the algorithm's low execution speed, an implementation of greedy algorithm for seam finding and usage of the Numba package are vital in reducing execution time significantly.

2. Literature Review

The traditional seam carving, proposed by Shai Avidan and Ariel Shamir (2007), uses a backward energy function to define the importance of a pixel. However, after a seam was removed, causing a redistribution of pixel values in the resized image, the energy function ignored the inserted energy for the pixels and used the previous energy map of the original image instead. This results in noticeable artifacts or distortions in the resized image. And so, a year later, the authors of the first paper on seam carving proposed the forward energy function, which considers the impact of seam removal on neighboring pixels (Avidan & Shamir, 2009). On the other hand, Noh and Han (2012) proposed an energy function based on the forward gradient differences for seam carving in both orientation and magnitude before and after the removal of a seam. This results in preserving regular structures, i.e., straight lines and smooth curves. The improved seam carving is efficient but slower than the original algorithm.

The forward and backward energy functions both have their own benefits. But in spite of that, damage to local structure (or image features) and to the global visual effect (or overall appearance or composition of the image) occurs frequently in seam carving since the algorithm repeatedly removes seams until the desired image size is reached without considering the real visual effect (Lin et al., 2014). In addition, Garg et al. (2014) investigated seam carving and simulated the aliasing effect of increasing image size. The optimal seam is calculated and replicated to be inserted into the image as a fraction of the original enlarged image size. Extreme seam insertion causes an aliasing effect, which can degrade the image's overall visual appearance.

Seam carving algorithm uses dynamic programming to find the optimal seam or minimum seam cost in the image (Garg & Negi, 2020). Given that dynamic programming requires many iterations, computing the optimal seam by pixel by pixel, the seam carving algorithm’s process of inserting and deleting seams is time consuming (Lin et al., 2014; Garg et al., 2014). Meanwhile, a block-based seam carving (BSC) approach was introduced by Mishiba and Ikehara (2011), where “a seam element is a pixel block, and a seam is a path of blocks." Instead of removing seams, downsampling the block of seams is done, which reduces the pixel's width and creates fewer distortions than seam carving. In contrast to the traditional SC, which decreases the image's width one pixel at a time, BSC shrinks the image's width in one process. This makes BSC faster than seam carving. However, there are some cases where the resizing results have artifacts.

Entropy, a concept in image processing, quantifies the uncertainty or complexity of an image or signal. Tsai et al. (2007) use the Shannon entropy, focusing on transmitted information (TI) as a single, unified metric for assessing the quality of digital radiographic images. Meanwhile, Kao and Nutter (2006) proposed a novel image resizing technique called the Maximum Entropy Algorithm (MEA), which is designed specifically for biomedical imaging applications, it works by selecting the most informative pixel from each local neighborhood. There are multiple variations of entropies created, as by Ribeiro et al. (2021). Among the many forms of entropy developed, Shannon entropy, differential entropy, Tsallis entropy, sample entropy, approximate entropy, and permutation entropy have been the most frequently cited in the literature. In recent years, permutation and sorting-based entropies have shown the most significant growth in impact on scientific works.

According to Manis et al. (2017), bubble entropy quantifies sorting effort (number of swaps) using bubble sort to compute pixel entropy, replacing Shannon's entropy in generating an importance map for improved seam carving. By eliminating the r parameter and minimizing the impact of m, it simplifies parameter tuning while enhancing efficiency and stability. On the other hand, Achanta and Sabine (2009) found that the traditional grayscale intensity gradient maps only show higher energy at the edges, which is sensitive to noise and deformations on salient objects. Thus, rather than just the edges or texture regions, they proposed a saliency detection scheme based on seam carving to generate a map that assigns saliency values to the entire salient region and is computed only once. Similarly, Tian et al. (2007) introduced a saliency-based approach for change detection in remote sensing images using an improved Itti visual saliency model. The emphasis on feature fusion and robustness illustrates saliency maps' effectiveness in discerning visually meaningful areas, echoing the goals of seam carving algorithms. Since seam carving seeks to remove non-salient pixels while preserving content integrity, such saliency-driven techniques reinforce the importance of accurately modeling visual attention in spatial transformations.

This study computes the importance map with the image in the CbxCr channel. Dargham et al. (2018) analyzed the performance of individual channels of the YCBCR color space relative to gray scale images in face recognition applications, and further in particular in surveillance applications. Results show that although gray scale always outperforms each individual YCBCR channel, the combination of CBxCR with another channel perform better than gray scale performance in certain training conditions. Another method used to compute the importance map is haar-wavelet edge detection. Fan et al. (2007) proposed a differential Haar-Gaussian (DHG) wavelet transform with a bandwidth matching algorithm to accurately detect edges. The proposed scheme is especially suitable for images taken with telecentric optics, which have to be wide depth of focus. Method capable of mitigating blur from defocus and thus does not sacrifice accuracy in terms of edge measurement across multiple defocus situations. Experimental data points to the fact that this approach does not compromise the accuracy of the measurement, leakage below 0.22% even for large defocused distances. In another study, the use of wavelet transforms in image processing effectively reduces computational requirements while maintaining high image quality (Liaw et al., 2020). Low-pass filtering helps focus on essential features, while high-pass components adjust disparities, improving performance and accuracy. Researchers have noted that adaptive selection of window sizes based on edge information further enhances disparity calculations, leading to better matching accuracy and fewer errors, while ensuring that important image details are preserved during estimation.

With respect to improving performance, this study applies the Just-In-Time (JIT) compilation and greedy algorithm for faster seam carving. According to Brock et al. (2018), JIT compilation dynamically converts code into machine language during runtime, aiming to improve execution speed for frequently used ("hot") code sections. Traditional JIT compilation policies often rely on simplistic metrics, such as invocation counts, to determine which methods to compile. JIT compilation plays a pivotal role in improving the runtime performance of dynamic programming languages by compiling hot sections of code on the fly. This process enables applications to achieve execution speeds closer to those of statically compiled languages while maintaining the flexibility of dynamic execution. According to Jant and Kulkarni (2013), JIT compilation bridges the gap between the flexibility of interpreted execution and the performance of statically compiled languages. In modern JIT systems, optimization phases play a crucial role in determining the quality of the compiled code, directly impacting execution speed, memory usage, and energy consumption. In addition, Kawakibi (2022) proposed an implementation of the greedy seam carving algorithm that seeks to reduce memory overhead while maintaining quality, albeit with potential trade-offs concerning the global optimality of the seams selected. The Sobel operator plays a pivotal role in defining energy functions, and its application for edge detection remains a foundational component in enhancing seam carving approaches.

Several methods have been proposed to address the challenges of content-aware image and video retargeting. Traditional downscaling like cropping and scaling (CR & SCL), which uniformly reduces all image elements, often makes small objects harder to discern (Pal et al., 2016). SC removes or duplicates seams of pixels to resize images, but can introduce noticeable jags in structural objects (Rubinstein et al., 2008). Warping methods (WARP) deform a grid mesh to fit new dimensions, but may suffer from edge flipping or fail to preserve prominent lines (Wolf et al., 2007). Shift-map editing (SM) represents image editing operations as a graph labeling problem, but may not always capture user intentions (Pritch et al., 2009). Multi-operator approaches (MULTIOP) combine different operators, SC, SCL, and CR for improved results, but the optimization can be computationally expensive (Rubinstein et al., 2009). These methods have limitations, such as potential distortion of important features, artifacts in homogeneous regions, or high computational complexity.

Zhang et al. (2018) proposed the Learned Perceptual Image Patch Similarity (LPIPS) metric, which uses deep network features to measure perceptual similarity between images. Deep features from various networks correlate better with human visual similarity judgments than traditional metrics like SSIM and PSNR. By calibrating deep embeddings with human perceptual data, LPIPS provides a more reliable and human-aligned image quality assessment across distortions and real-world image processing tasks. On the other hand, Wang et al. (2003) proposed the Multiscale Structural Similarity Index (MS-SSIM). This method improves the original SSIM by measuring quality of images at different scales, which increases precision depending on factors like view distance and resolution. This also points out issues with many conventional measures, including Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE), and their discrepancies with human perception. MS-SSIM is a more accurate quantitative description of the differences between images as perceived by the human visual system, and therefore gives more relevance to the assessment of image quality.

Su et al. (2023) also introduced a self-adaptive hyper network architecture for BIQA, which separates the assessment process into three stages: content understanding, perception rule learning, and quality prediction. By adaptively establishing perception rules from extracted image semantics, the model estimates image quality in a self-adaptive manner, enhancing its generalization to a wide range of image types. Experiments show that this approach outperforms state-of-the-art methods on authentic image databases while also performing competitively on synthetic datasets.

Chen et al. (2023) also proposed a unimodal deep model based top-down IQA approach by learning from deep multi-scale features. Their method consists of a heuristic coarse-to-fine attention network, called CFANet. Imitating the human visual system (HVS) flow, the process in which semantic information is progressively passed from highest level down to lowest level in the HVS is reproduced in this system. This heuristic design circumvents the complexity of choosing between multiple features from different scales and has been found to be successful. CFANet is available for Full-Reference (FR) and No-Reference (NR) IQA. They employ ResNet50 as its backbone and show that CFANet performs better or approximately the same as (the state of the art) on most public FR and NR benchmarks as those methods based on vision transformers, yet they are much more efficient (an estimate of ~13% of the FLOPS for the state of the art FR method).

3. Methodology

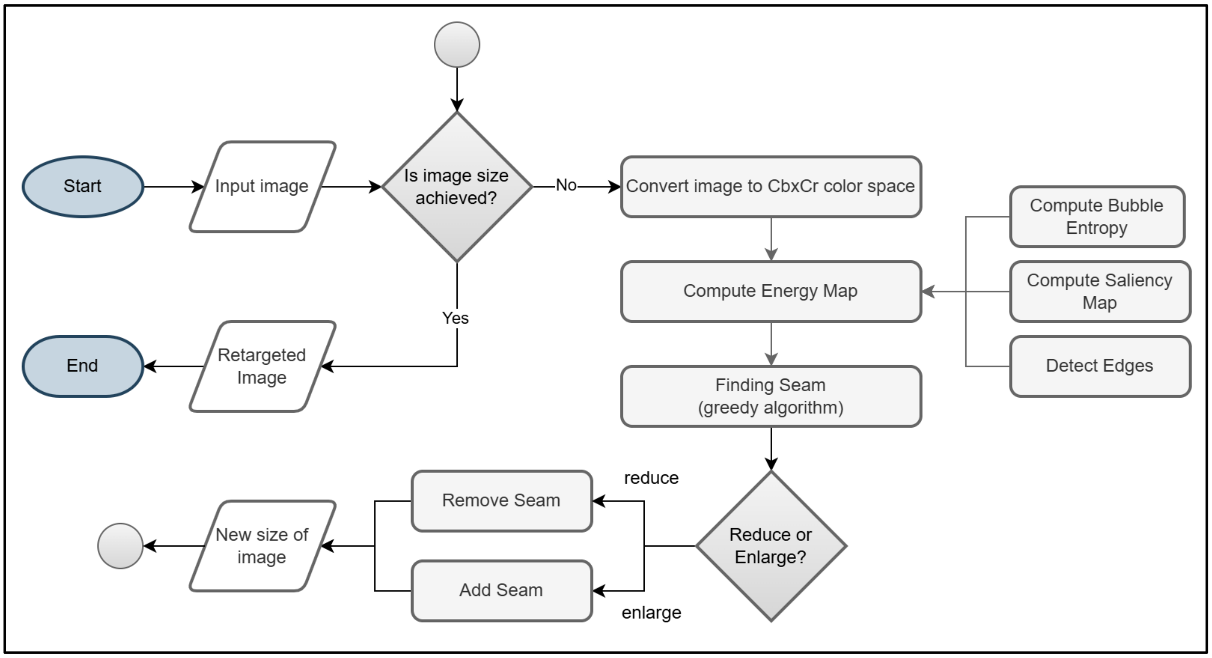
3.1. Research Design

This study employs an experimental and computational research design to develop and evaluate the enhanced seam carving algorithm. The approach involves implementing and testing modifications such as Haar wavelet edge detection, bubble entropy, and saliency detection for improved energy map generation. The design enables evaluation of the proposed method against traditional seam carving techniques based on quantitative performance metrics, such as preservation of salient image content, computational efficiency, and visual quality. This approach ensures that the effectiveness of the enhancements can be objectively assessed and compared to existing methods.

Figure 1 represents the methodology of the enhanced seam carving algorithm for content-aware image resizing. It visually outlines the sequential steps involved in processing an image, computing an optimized energy map, and performing seam removal or addition based on the resizing requirements.

Figure 1

Flowchart of the proposed algorithm



Source*:* draw.io website was used to make this figure

It begins with the input image checking if the desired size is achieved, if not, we convert the image to its CbxCr color space and use it for the computation of the energy map. The energy map combines the image's computed bubble entropy (BEn), saliency map, and edges. With the computed energy map, the greedy algorithm is applied to identify the least important seam (path of pixels with the lowest energy). It then determines whether to reduce or enlarge the image so it can either remove or add the identified seam. The process repeats from the step of computing the energy map until the image reaches the required dimensions.

3.2. Hardware and Software Requirements

Experiments were done online in the google colab environment with the following system specifications: CPU model of Intel(R) Xeon(R) CPU @ 2.20GHz and 13GB memory. The algorithm was implemented using the Python language and it utilizes various Python libraries to facilitate image processing, mathematical computations, and performance optimization. The PyWavelets (pywt) is employed for Haar wavelet edge detection, which helps in refining the energy map. Image conversion utilities such as color transformations, float conversions, loading and saving of images are done with OpenCV (cv2) and scikit-image (skimage) library. NumPy (numpy) supports efficient numerical operations and matrix manipulations, it also goes hand in hand with the Numba package which accelerates computation-heavy tasks by just-in-time (JIT) compilation, optimizing loops and array operations for improved performance. These dependencies collectively enhance the efficiency and accuracy of the seam carving process. On the other hand, the perf_counter() method from the time library was used to benchmark the execution time of the proposed algorithm.

3.3. RetargetMe Dataset

This dataset contains all the images and retargeted results of other resizing algorithms from the study of Rubinstein et al. (2010). It is composed of 80 images with some images retargeted using methods such as cropping (cr), multi-operator (multiop), seam carving (sc), scaling (scl), shift-maps (sm), scale-and-stretch (sns), streaming video (sv), energy-based deformation (LG), and nonhomogeneous warping (warp). Most of the retargeted images are reductions in width; thus, the removal of seams on width is used for comparison. There are other retargeting methods in the dataset not mentioned; however, not all images in the dataset were retargeted using those methods. Only the methods mentioned, excluding energy-based deformation (LG), are used for comparison, comprising 61 images from the dataset.

3.4. Performance Metrics

Using Chen and Mo’s (2022) PyTorch toolbox for image quality assessment, or PYIQA, two (2) full-reference (FR) metrics and two (2) no-reference (NR) metrics were chosen to evaluate the proposed method: LPIPS for symmetric (VGG net) and asymmetric (VGG+ net) images by Zhang et. al. (2018), MS-SSIM by Wang et. al. (2003), HyperIQA by Su et. al. (2020), and TOPIQ by Chen et. al. (2023), respectively.

The LPIPS metrics was proposed by Zhang et al. (2018), it uses deep network features to measure perceptual similarity between images and provides a human-aligned image quality assessment. On the other hand, Wang et al. (2003) introduced the MS-SSIM, which improves the accuracy of traditional SSIM under various conditions like resolution and viewing distance. MS-SSIM better reflects how visual system interprets information, offering a more meaningful evaluation of image quality. Meanwhile, Su et al. (2021) proposed a self-adaptive hyper network for blind image quality assessment in the wild. It separates the task into content understanding, perception rule learning, and quality prediction, improving performance on diverse, real-world distortions by dynamically adapting quality assessment based on image content. Lastly, Chen et al. (2023) introduced TOPIQ using CFANet. By leveraging cross-scale attention, the method guides focus on important local distortions based on high-level semantics, achieving efficient, human-like quality predictions across various benchmarks.

4. Findings and Discussion

This section presents the experimental results with 61 images from the RetargetMe dataset and discusses the effectiveness of the proposed enhanced seam carving algorithm based on image quality assessment and computational efficiency. The results are analyzed using full-reference and no-reference image quality metrics, as well as execution time comparisons with and without Numba JIT optimization.

4.1. Image Quality Assessment

To evaluate the quality of the retargeted images, full-reference metrics LPIPS-VGG, LPIPS+VGG, and MS-SSIM were used. The full reference metrics requires the images, retargeted image and original image, to be the same resolution (width x height). Thus, two tables have been generated to resize both images to the retargeted image's size (table 1) and original image's size (table 2). As full-reference metrics scale the images to the same size, it would be safe to assume that the scaling method would outperform any other methods. To avoid bias, methods that use scaling such as multi-operator (multiop) and scaling (scl) itself are removed from the assessment.

In LPIPS-based metrics, lower values indicate better image quality, while in MS-SSIM, higher values are preferred. The results show that the proposed method (ours) outperforms existing methods, achieving the lowest LPIPS values and the highest MS-SSIM for both retargeted image-size based (table 1) and original image-size (table 2) based metrics values, suggesting better preservation of perceptual quality.

Table 1

Retargeted image size-based full-reference metrics values

	LPIPS-VGG		LPIPS+-VGG		MS-SSIM	
Method	**Mean**	**Std.**	**Mean**	**Std.**	**Mean**	**Std.**
cr	0.511421	0.065614	0.531789	0.06136	0.425474	0.09988
sc	0.413225	0.086541	0.430218	0.083127	0.49353	0.132954
sm	0.510556	0.076351	0.528083	0.073383	0.387395	0.114567
sns	0.473239	0.077917	0.501528	0.083131	0.42324	0.115056
sv	0.40233	0.098679	0.42828	0.108519	0.509366	0.135113
warp	0.355387	0.110557	0.376038	0.111377	0.554840	0.149486
ours	0.348672	0.092663	0.372872	0.093622	0.583237	0.147726

***Legend**:* In LPIPS, the lower the values the better. While in MS-SSIM, the higher the values the better. First best is highlighted in red, while the second best is highlighted in blue.

Table 2

Original image size-based full-reference metrics values

	LPIPS-VGG		LPIPS+-VGG		MS-SSIM	
Method	**Mean**	**Std.**	**Mean**	**Std.**	**Mean**	**Std.**
cr	0.524337	0.066468	0.549173	0.062792	0.43914	0.098799
sc	0.438204	0.086051	0.459456	0.083196	0.503262	0.126168
sm	0.527124	0.075235	0.549071	0.071732	0.409782	0.11113
sns	0.494168	0.078598	0.526216	0.083652	0.434266	0.110186
sv	0.434657	0.096772	0.464339	0.10721	0.509695	0.130417
warp	0.396247	0.104356	0.421251	0.107135	0.562668	0.137215
ours	0.376636	0.097604	0.406796	0.098706	0.588743	0.139395

***Legend**:* In LPIPS, the lower the values the better. While in MS-SSIM, the higher the values the better. First best is highlighted in red, while the second best is highlighted in blue.

For no-reference metrics (table 3), HyperIQA and TOPIQ were used to assess the overall quality without a ground truth reference. This means only the retargeted images are assessed without needing to use the original images for reference.

The results indicate that the proposed method achieves competitive scores, with 0.678812 in HyperIQA and 0.680138 in TOPIQ, ranking among the best methods. These findings suggest that the enhanced seam carving approach maintains structural consistency and perceptual quality in the resized images.

Table 3

No-reference metrics values

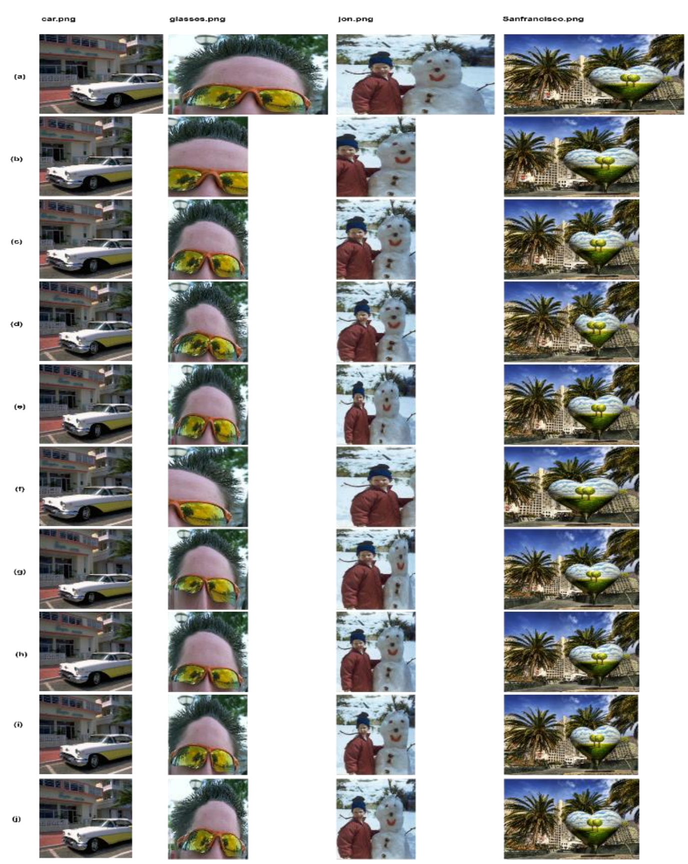
Time	LPIPS-VGG		MS-SSIM	
Method	**Mean**	**Std.**	**Mean**	**Std.**
cr	0.665145	0.091607	0.676049	0.097707
multiop	0.683985	0.086856	0.694194	0.092259
sc	0.671163	0.086695	0.677899	0.096204
scl	0.673183	0.081991	0.683191	0.091897
sm	0.636631	0.090089	0.639643	0.099257
sns	0.652248	0.08576	0.66124	0.093155
sv	0.649704	0.083086	0.657748	0.089017
warp	0.630816	0.089117	0.627769	0.098226
ours	0.678812	0.083474	0.680138	0.092839

Legend: The higher the values the better. First best is highlighted in red, while the second best is highlighted in blue.

A side-by-side comparison of images (car1, glasses, jon, and Sanfrancisco) from the RetargetMe dataset is resized using different methods is shown in figure 1.

Figure 1

Image comparisons



Note: (a) original image, (b) cr, (c) multiop, (d) sc, (e) scl, (f) sm, (g) sns, (h) sv, (i) warp, (j) ours

The proposed method (ours) preserves important image structures while avoiding excessive distortions and artifacts.

4.2. Computational Efficiency

To assess performance improvements, the execution time of the seam carving process was compared with and without Numba JIT optimization (table 4). Five (5) images from the RetargetMe dataset were chosen for evaluation: car1, car2, face, getty, and surfers.

Table 4

Time execution in seconds

				Without Numba JIT		With Numba JIT		
Image	**Width**	**Height**	**No. of seams**	**T(s)**	**T(s) / no. seams**	**T(j)**	**T(j) / no. seams**	**Change %**
car1	384	385	96	761.53778	7.9326852	60.738750	0.6326953	-92.0242
car2	500	375	125	1226.6987	9.8135901	107.58805	0.8607044	-91.2295
face	392	300	98	594.91162	6.0705268	44.753490	0.4566682	-92.4773
getty	500	334	125	1159.4086	9.2752693	84.838023	0.6787041	-92.6826
surfers	333	500	83	706.59558	8.5131998	54.762562	0.6597899	-92.2498
							Average	-92.1327

Legend: T / no. seams is equal to the time executed per seam. Change from T(s) to T(j) is computed.

The images without Numba JIT executed for 11 to 21 minutes in comparison to 44 seconds to 2 minutes range execution with Numba JIT. The results demonstrate a significant reduction in execution time. The proposed method reduces computational time by an average of 92.13%, highlighting the effectiveness of using Numba for accelerating the seam finding and energy map computations.

5. Conclusion

Content-aware image resizing techniques have advanced significantly over the years. In seam carving, enhancing the importance map can greatly improve the accuracy of the algorithm. This paper introduces a new importance map that integrates bubble entropy, a saliency map, and Haar wavelet edge detection to optimize image resizing within the seam carving framework. To evaluate the effectiveness of the proposed approach, experiments were conducted using the RetargetMe dataset, with results analyzed through quantitative metrics. Additionally, both full-reference and no-reference image quality assessments were performed for visual evaluation. The simulation results demonstrate that the proposed method outperforms traditional seam carving techniques. For future improvements, object or face detection could be incorporated, as images containing faces are more prone to distortion and visual artifacts. Moreover, utilizing a more advanced saliency map could enhance the detection of important regions. Machine learning and deep learning techniques may further refine the accuracy and efficiency of the proposed algorithm.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This research is supported by the Department of Science and Technology (DOST) through the DOST-SEI Undergraduate Scholarship.

Declaration

The author declares the use of Artificial Intelligence (AI) in writing this paper. In particular, the author used QuillBot in paraphrasing ideas and ChatGPT in summarizing key points. The author takes full responsibility in ensuring proper review and editing of contents generated using AI.

References

Achanta, R., & Susstrunk, S. (2009). Saliency detection for content-aware image resizing. *Sixteenth IEEE International Conference on Image Processing (ICIP)*. https://doi.org/10.1109/ICIP.2009.5413815

Avidan, S., & Shamir, A. (2007). Seam carving for content-aware image resizing. *In ACM SIGGRAPH 2007 Papers (SIGGRAPH '07)*. Association for Computing Machinery, New York, NY, USA, 10–es. https://doi.org/10.1145/1275808.1276390

Avidan, S., & Shamir, A. (2009). Seam carving for media retargeting. *Communications of the ACM, 52(1), 77–85*. https://doi.org/10.1145/1435417.1435437

Brock, J., Ding, C., Xu, X., & Zhang, Y. (2018). PAYJIT: Space-optimal JIT compilation and its practical implementation. *Proceedings of the 27th International Conference on Compiler Construction (CC'18), Vienna, Austria*, 71-81. https://doi.org/10.1145/3178372.3179523

Chen, L., Xie, X., Fan, X., Ma, W., Zhang, H., & Zhou, H. (2003). A visual attention model for adapting images on small displays. *ACM Multimedia Systems Journal, 9*(4), 353–364. https://doi.org/10.1007/s00530-003-0105-4

Dargham, J. A., Chekima, A., Moung, E. G., & Omatu, S. (2018). A comparison of the YCBCR colour space with gray scale for face recognition for surveillance applications. *Advances in Distributed Computing and Artificial Intelligence Journal, 7*(2), 35-42. https://doi.org/10.14201/ADCAIJ2018724352

Fan, L., Song, F., & Jutamulia, S. (2007). Edge detection with large depth of focus using differential Haar–Gaussian wavelet transform. *Optics Communications, 270*(1), 169–175. https://doi.org/10.1016/j.optcom.2006.09.015

Garg, A., & Negi, A. (2020). A survey on content-aware image resizing methods. *KSII Transactions on Internet and Information Systems, 14*(7). https://doi.org/10.3837/tiis.2020.07.015

Jantz, M. R., & Kulkarni, P. A. (2013). Performance potential of optimization phase selection during dynamic JIT compilation. *Proceedings of the 9th ACM SIGPLAN/SIGOPS International Conference on Virtual Execution Environments* (VEE '13), 131–140. https://doi.org/10.1145/2451512.2451539

Kao, P. B., & Nutter, B. (2006). Application of Maximum Entropy-Based Image Resizing to Biomedical Imaging. *19th IEEE Symposium on Computer-Based Medical Systems (CBMS'06)*. https://doi.org/10.1109/cbms.2006.46

Kawakibi, Z. M. (2022). Content-aware image resizing using a greedy seam carving algorithm. *Makalah IF2211 Strategi Algoritma, Semester II Tahun 2021/2022*.

Liaw, J.-J., Lu, C.-P., Huang, Y.-F., Liao, Y.-H., & Huang, S.-C. (2020). Improving Census Transform by High-Pass with Haar Wavelet Transform and Edge Detection. *Sensors*, 20(9), 2537. https://doi.org/10.3390/s20092537

Lin, X., Ma, Y., Ma, L., & Zhang, R. (2014). A survey for image resizing. *Journal of Zhejiang University SCIENCE C, 15*(9). https://doi.org/10.1631/jzus.C1400102

Manis, G., Aktaruzzaman, M., & Sassi, R. (2017). Bubble entropy: An entropy almost free of parameters. *IEEE Transactions on Biomedical Engineering, 64*(11), 2711-2718. https://doi.org/10.1109/TBME.2017.2664105

Mishiba, K., & Ikehara, M. (2011). Block-based seam carving. *2011 1st International Symposium on Access Spaces (ISAS)*. https://doi.org/10.1109/ISAS.2011.5960930

Noh, H., & Han, B. (2012). Seam carving with forward gradient difference maps. *Proceedings of the 20th ACM International Conference on Multimedia*, 709-712. https://doi.org/10.1145/2393347.2396293

Pal, R., & Tripathi, P. C. (2016). Content-aware image retargeting: A survey. In R. Pal (Ed.), *Innovative research in attention modeling and computer vision applications* (pp. 115-131). IGI Global. https://doi.org/10.4018/978-1-4666-8723-3.ch005

Polson, W. (2025, January 2). Common screen resolution for web design in 2025. *Australian Internet Advertising*. https://aiad.com.au/what-screen-resolution-should-one-design-for/

Pritch, Y., Kav-Venaki, E., & Peleg, S. (2009). Shift-map image editing. *2009 IEEE 12th International Conference on Computer Vision, 151-158*. https://doi.org/10.1109/iccv.2009.5459159

Ribeiro, M., Henriques, T., Castro, L., Souto, A., Antunes, L., Costa-Santos, C., & Teixeira, A. (2021). The Entropy Universe. *Entropy, 23(2), 222*. https://doi.org/10.3390/e23020222

Rubinstein, M., Shamir, A., & Avidan, S. (2008). Improved seam carving for video retargeting. *ACM Transactions on Graphics, 27*(3), 16. https://doi.org/10.1145/1360612.1360615

Rubinstein, M., Shamir, A., & Avidan, S. (2009). Multi-operator media retargeting. *ACM Transactions on Graphics, 28*(3), 23. https://doi.org/10.1145/1531326.1531329

Suh, B., Ling, H., Bederson, B. B., & Jacobs, D. W. (2003). Automatic thumbnail cropping and its effectiveness. *Proceedings of the 16th annual ACM symposium on User Interface Software and Technology (UIST '03),* 95–104. https://doi.org/10.1145/964696.964707

Tian, M., Wan, S., & Yue, L. (2007).A novel approach for change detection in remote sensing image based on saliency map. *In Proceedings of the IEEE International*

Conference on Computer Graphics, Imaging and Visualisation (CGIV) (pp. 397–402). IEEE. https://doi.org/10.1109/CGIV.2007.11

Tsai, D.-Y., Lee, Y., & Matsuyama, E. (2007). Information Entropy Measure for Evaluation of Image Quality. *Journal of Digital Imaging, 21(3), 338–347*. https://doi.org/10.1007/s10278-007-9044-5

Wang, Y.-S., Tai, C.-L., Sorkine, O., & Lee, T.-Y. (2008). Optimized scale-and-stretch for image resizing. *ACM Transactions on Graphics*, *27*(5), 118. https://doi.org/10.1145/1409060.1409071

Wolf, L., Guttmann, M., & Cohen-Or, D. (2007). Nonhomogeneous content-driven video-retargeting. *Proceedings of the Eleventh IEEE International Conference on Computer Vision (ICCV)*. https://doi.org/10.1109/ICCV.2007.4409010

Zhang, Y. F., Hu, S. M., & Martin, R. R. (2008). Shrinkability maps for content-aware video resizing. *Computer Graphics Forum*, *27*(7), 1797–1804. https://doi.org/10.1111/j.1467-8659.2008.01325.x