# Enhanced Seam Carving via Integration of Energy Gradient Functionals

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***Abstract*—This letter proposes an improved seam carving approach for content-aware image retargeting. The proposed algorithm extends upon the backward and forward energy cost functionals used in previous seam carving methods by incorporating an energy gradient cost functional in the optimization process. This combined *absolute* energy cost functional penalizes seam candidates that cross areas of local extrema, which characterizes regions with high concentrations of "important" image detail. Experiments show superior visual quality results using the proposed absolute energy cost functional over existing methods on a variety of images characterized by high image detail concentration.**

***Index Terms*—Energy gradient, image retargeting, seam carving.**

## I. Introduction

IMAGE retargeting is the process of adapting image content for different display conditions, and has been become increasingly important in recent years due to the diversity of screen sizes and resolutions used in devices that display digital media. Traditional image resizing techniques can introduce noticeably visible distortions in the content of an image when it is being resized to fit different aspect ratios and screen sizes. To minimize these distortions, more content-aware image retargeting techniques have been proposed to better preserve important image content in the adapted image. Such image retargeting methods include attention model based methods [1], [2], nonlinear data dependent scaling approaches [3], segmentation based approaches [4], local saliency-based approaches [5], and object-based approaches [6].

Recently, an interesting approach for image retargeting is the concept of seam carving [7]–[9], [11], [12], where monotonic and connected paths of pixels known as *seams* are identified based on the underlying detail and characteristics of the image. By removing seams from the image, the image size is reduced while the important detail within the image is preserved. This approach has proven to be very effective at producing visually pleasing images that maintain important image detail from the original image, and has been extended for video retargeting [8] and combined with scaling and cropping operators [10]. Furthermore, extensions have been made to improve edge preservation and decrease artifacts [11]. A limitation exhibited by existing seam carving approaches is the presence of noticeable visual artifacts when dealing with images with high image detail concentration.

The main contribution of this letter is an improved seam carving approach for content-aware image retargeting that is designed to better handle images characterized by high image detail concentration. A new *absolute* energy cost functional is introduced that combines backward energy, forward energy, and an additional energy gradient cost functional into the optimization process to determine appropriate seams for removal. The proposed energy cost functional is investigated and observed to show visual improvements when used on images containing a high concentration of important image features.

While both aim to reduce the presence of artifacts, the proposed energy cost functional differs significantly from that proposed in [11]. First, while the method in [11] relies only on the image gradient (change in pixel intensities), the proposed energy cost functional also takes advantage of the gradient of the energies itself (change in pixel energies). Second, the proposed energy cost functional is designed to deter seams while the method proposed in [11] takes a more stricter approach by prohibiting seams. As such, situations can arise where the method in [11] cannot achieve the desired image size due to the thresholding being affected by a high concentration of important image features, resulting in the need for additional cropping.

## II. Theory

The goal of seam carving is to identify a monotonic and connected path of pixels, denoted by seam $s$, that can be removed while preserving the underlying detail of the image. Therefore, by treating important image detail as pixels with high energy content, the problem of seam carving from an image $I$ can be viewed as the identification of an optimal connected pixel path $s$ that minimizes the total energy $E$ of the path

$$\begin{aligned} s &= \arg\min_s \{E(s)\} \\ &= \arg\min_s \left\{ \sum_{i=1}^{n} e(I(s)) \right\} \end{aligned} \tag{1}$$

where $n$ is the number of pixels in the seam, and $e$ is the energy of a particular pixel. A typical measure of energy used in seam carving is defined by the $L_1$-norm of the gradient, which has been shown to provide visually pleasing results [7]:

$$e(I) = \left|\frac{\partial}{\partial x} I\right| + \left|\frac{\partial}{\partial y} I\right|. \tag{2}$$

Once a cumulative energy matrix for the image is defined based on the energy measure $e$, the optimal seam $s$ for removal

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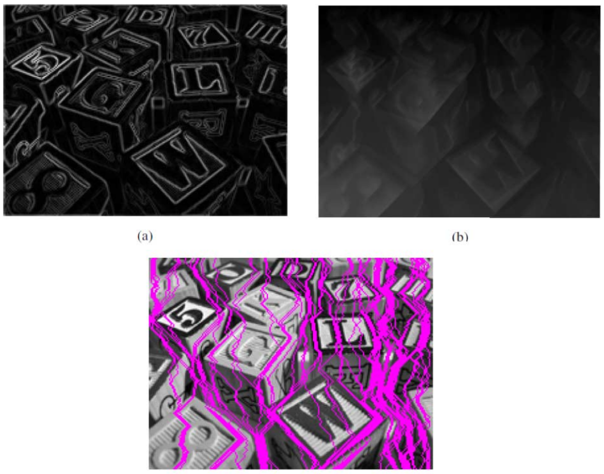


Fig. 1. Seam carving using the proposed absolute energy cost functional. (a) Energy of the image, (b) absolute energy matrix, and (c) energy seams removed after all iterations based on absolute energy cost functional.

is found as the seam that minimizes a cost functional for all possible seams in the image.

## III. Backward Energy Cost Functional

In [7], a dynamic programming approach is used to identify this optimal seam based on a backwards energy cost functional. The backward energy cost functional aims to find the seam which will remove the least amount of energy from the image when it is removed. Although an exponential number of seams exist, the minimal seam can be calculated using a dynamic programming approach by updating the cumulative energy matrix $e$ in-place based on a second-order Markov model [13] and the backward energy cost functional as

$$e(i,j) = e(i,j) + \min(e(i-1,j-1), e(i-1,j), e(i-1,j+1)). \tag{3}$$

where $(i,j)$ defines the location of a particular pixel. At the end of the updating process, the minimal cost seam can be found by backtracking from the smallest element in the last row of the updated cumulative energy matrix. A similar dynamic programming approach can be used to determine the horizontal seams, although the horizontal and vertical indices must be updated as appropriate.

## IV. Forward Energy Cost Functional

In [8], the dynamic programming approach was extended to make use of an improved forward energy cost functional. This energy cost functional extends the backward energy cost functional by also taking into account the amount of energy inserted into the image through the removal of a seam. The inserted energy comes from new structures formed via the seam removal process by joining pixels that were previously disjoint. As in the backward energy case, the minimal seam can be calculated using a dynamic programming approach by updating the cumulative energy matrix $e$ in-place as

$$e(i,j) = e(i,j) + \min\begin{pmatrix} e(i-1,j-1) + C_L(i,j), \\ e(i-1,j) + C_U(i,j), \\ e(i-1,j+1) + C_R(i,j) \end{pmatrix} \tag{4}$$

where $C_L$, $C_U$, and $C_R$ are the forward energy functionals defined by

$$C_U(i,j) = |I(i,j+1) - I(i,j-1)|, \tag{5}$$

$$C_L(i,j) = C_U(i,j) + |I(i-1,j) - I(i,j-1)|, \tag{6}$$

$$C_R(i,j) = C_U(i,j) + |I(i-1,j) - I(i,j+1)|. \tag{7}$$

## V. Absolute Energy Cost Functional

The proposed *absolute* energy cost functional attempts to better handle images with high image detail concentration by taking into account the energy gradient along the seams being removed. This is accomplished by incorporating the energy gradient alongside the backward and forward energy functionals into the dynamic programming process, giving us the following cumulative energy matrix update formulation,

$$\begin{aligned} e(i,j) = {} & e(i,j) + |e(i,j+1) - e(i,j)| \\ & + |e(i+1,j) - e(i,j)| \\ & + \min\begin{pmatrix} e(i-1,j-1) + C_L(i,j), \\ e(i-1,j) + C_U(i,j), \\ e(i-1,j+1) + C_R(i,j) \end{pmatrix}. \end{aligned} \tag{8}$$

The additional of the energy gradient cost functional is designed to ensure that seams do not cross through areas that contain local extrema. This is due to the fact that even minor local extrema require an energy gradient to be considered a minimum or maximum, and thus considering this energy gradient should help accentuate even seemingly insignificant extrema. As such, it can be said that the proposed absolute energy cost functional takes a very conservative approach when determining areas of the image to remove. It should be noted that a forward difference approximation for the energy gradient was chosen in the proposed absolute energy cost functional as other approximations would not allow an in-place update of the energy matrix $e$. By taking a forward difference approximation, the amount of computation time and storage space required for the calculations is greatly reduced, while the observed impact of using this approximation was determined to be negligible through experimentation.

As with the other energy cost functionals, the seam is determined through a backtracking step once the entire cumulative energy matrix has been updated. The absolute energy cost functional can also be applied to locate horizontal seams once the necessary indices have been modified. Once the minimal cost seam is found, the seam carving operator removes the seam from the image by going through each row and shifting all pixels right of the seam one position to the left. Once all rows have been shifted, the rightmost column of the image is dropped to give the proper dimension for the image. This process is iteratively applied to remove individual seams until the desired output dimensions have been reached. The overall process of seam carving

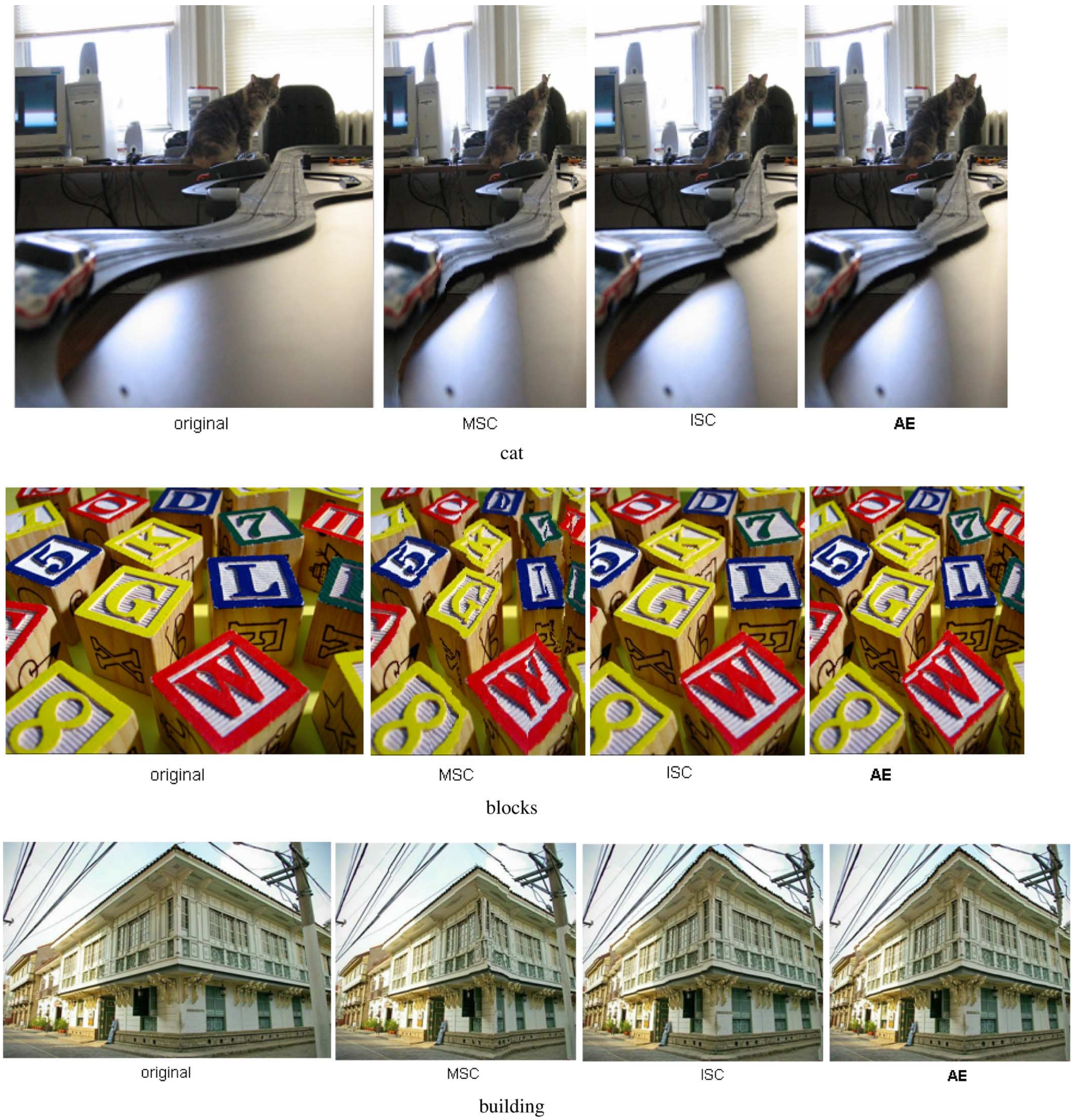


Fig. 2. Seam carving results for the tested images using MSC method [12], ISC method [11], and the proposed AE method.

using the proposed absolute energy cost functional is shown in Fig. 1.

## VI. Experimental Results

The seam carving approach using the proposed absolute energy (AE) cost functional described in Section V was implemented and applied to a series of images to investigate its performance for adapting the size of an image while preserving its image detail and visual quality. For comparison purposes, the state-of-the-art multiscale seam carving (MSC) [12] and improved seam carving (ISC) [11] methods were also tested. Since situations can arise where improved seam carving [11] alone cannot achieve the desired image size, additional cropping is performed on the result to achieve the desired image size. The test images used for testing contain varying amounts of image content in order to test the methods for images with high concentration of image detail.

The seam carving results for all three methods are shown in Fig. 2. The first test image consists of a cat and curved race track. There are noticeable visual distortions in the image produced using MSC at race track region at the vanishing point, the speakers, and especially the cat's head. In the image produced

Fig. 3. Seam carving results using absolute energy (AE) cost functional for images contaminated by Gaussian noise ($\sigma = 12$). It can be observed that the presence of noise does not have a significant effect on the performance of the proposed cost functional.

using ISC, there is noticeable visual distortions in the cat's body. More importantly, ISC failed to achieve the desired image size, and so cropping was needed and thus led to content loss at the borders such as the missing heating element and objects in the monitor. In the image produced using AE, there are noticeably better continuity in the middle connection region of the race track, and the race track details at the vanishing point as well as the cat are better preserved.

The second test image consists of a collection of colored blocks. The image produced by MSC contained significant visible distortions, with the letters on the blocks largely warped. This is particularly noticeable in the red "11," green "7," and blue "L" blocks, which have been warped beyond character recognition. The image produced by ISC contained the least amount of warping, but that is due to the fact that ISC failed to achieve the desired image size and additional cropping is needed. As such, a lot of important content is missing at the boundaries, such as the entire red "11" and yellow "1" blocks, as well as the cherry on the red block to the left. Finally, the image produced using AE contains significantly less visual distortions when compared to MSC, while preserving more image content than ISC. The third test image consists of a building with lots of windows at the corner of an intersection surrounded by power lines. Significant visible distortions can be seen in the image produced using MSC, with the windows in the middle heavily warped. Both the results produced using ISC and AE exhibit little visible distortions.

An important area to investigate is on whether the introduction of the absolute energy (AE) cost functional would hurt seam carving performance when dealing with images contaminated by noise. To achieve this, the last two test images were contaminated by Gaussian noise with zero mean and a standard deviation of $\sigma = 12$. As seen in Fig. 3, the presence of noise does not have a significant effect on the performance of the proposed cost functional.

## VII. Conclusion

An improved seam carving approach was proposed for the purpose of content-aware image retargeting. An absolute energy cost functional was introduced that incorporates energy gradient information into the optimization framework to better account for areas of local extrema that characterizes high detail concentration. Experiments using color images with varying concentrations of image detail show that the proposed approach has potential for producing images with fewer visual distortions and artifacts. Future work involves the design of more robust multiscale energy functions that better characterize the underlying image details and characteristics, which can potentially further reduce the presence of visual distortions and artifacts.

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