

Hybrid local intensity variation and edge features map-based multi-focus image fusion using Genetic algorithm

¹Noor Khalid Ibrahim, ²Muthana S. Mahdi, ³Basim kudaer Abbas

¹Department of Computer Science, College of Science, Mustansiriyah University– Baghdad, Iraq

²Department of Computer Science, College of Science, Mustansiriyah University– Baghdad, Iraq

³Department of Computer Science, College of Science, Mustansiriyah University– Baghdad, Iraq

Article information

Article history:

Received: February, 3, 2026

Accepted: March, 17, 2026

Available online: March, 25, 2026

Keywords:

multi-focus,
GA,
patch fusion,
standard deviation filter,
Sobel.

*Corresponding Author:

Muthana S. Mahdi

muthanasalih@uomustansiriyah.edu.iq

DOI:

<https://doi.org/10.61710/kjcs.v4i1.154>

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Abstract

This study proposes a multi-focus image fusion approach that considers Genetic Algorithm (GA) optimization to achieve the selection of the most appropriate fusion weights that are used to increase the quality of the resulting fused image. local intensity variations with a standard deviation filter used to extract texture features, edge detection with the Sobel operator is defined, and a variance feature is also determined. The optimized weights are used to identify the best combination of feature maps of these three extracted features to achieve an accurate fusion process. Experiments demonstrate that this approach successfully retains texture, edges, and variation, resulting in a fused image with improved visual quality and information richness, as achieved in 66.7529, 105.4815, 0.6042, and 22.1658 with standard deviation, mean, SSIM, and PSNR, respectively.

1. Introduction

Cameras have suffered from focus issues due to the narrow depth of field (DOF) of their optical lenses, resulting in only certain parts of an image being in focus. Objects at different distances from the lens appear blurry, whereas those at the correct focus distance are captured clearly [1]. Image fusion is the process of combining relevant elements from two or more images of a scene to generate a single, highly informative image. For machine or human perception, the fused image should have more detailed information [2]. The multi-focus image fusion method combines images taken with different sensors, each focusing on different objects in a scene, to create a single image that captures all objects in focus [3]. It is essential in a wide range of applications, including machine vision, remote sensing, and medical imaging. Over the past decade, two types of fusion techniques have emerged: transform domain-based approaches and spatial frequency-based approaches [4].

The contribution of this paper is:

- 1- Multi-feature construction of multi-focus image fusion, which combines texture, edge, and local variance data to better detect focus and to improve the accuracy of the fusion.
- 2- The use of an adaptive optimization model via a genetic algorithm, which can automatically compute the optimal feature weights by maximizing entropy.

The rest of the paper is presented in explain methodology along with steps and figures in section 2, then Experimental Results and discussion are explained in section 3, followed by the conclusion in section 4.

2. Related Works

In this field, many algorithms have been proposed to achieve multi-focus image fusion as an algorithm to fuse the images by employing a fusion rule. In [5], A multi-scale generative adversarial network (MsGAN)-based end-to-end multi-focus image fusion technique is presented that fully utilizes image features by combining multi-scale decomposition with a convolutional neural network. Additionally, a multi-focus image fusion technique is presented in [6], which suggests using super pixels, locally linked pixels with similar colors and patterns, to differentiate the focused and de-focused areas of an image. In [7], a high-resolution real-time multi-focus image fusion algorithm based on multi-aggregation is proposed, where a Difference-of-Gaussians image and a Laplacian pyramid are used for focused-region detection. Further, the authors in [8] describe a method for multi-focus image fusion that employs a genetic algorithm (GA) to determine optimal weights from the entire image's edges, rather than dividing it into pyramid-shaped blocks. While the authors in [9] combine an enhanced Genetic Algorithm (GA) with the Elite Strategy and integrate it with the discrete wavelet transform (DWT), this work suggests an optimal genetic algorithm-based wavelet image fusion approach for printed circuit board (PCB) identification. In [10], to produce fully focused FFOA images, an FFOA image fusion method based on the nonsubsampling contourlet transform and contrast spatial frequency is proposed. A multi-focus image fusion technique is offered in [11] to implement the creation of an all-in-focus image from many microscopic images. The source images are first subjected to a bandpass filter. Laplacian transformation and thresholding with a morphological operation are then used to extract the focus regions. The natural connections between local focus images are then subjected to a self-adjusting guided filter. Table 1 explains a summary of these related works.

Table (1): Summary of Related Works in Multi-Focus Image Fusion

Reference	Year	Method	Techniques
[5]	2022	MsGAN-based end-to-end multi-focus image fusion	Multi-scale decomposition, CNN, GAN
[6]	2021	Super pixel-based multi-focus fusion	Super pixels for region segmentation
[7]	2025	Real-time high-resolution fusion using multi-aggregation	Difference of Gaussians (DoG), Laplacian pyramid
[8]	2017	GA-based multi-focus fusion	Genetic Algorithm using global edge information
[9]	2025	Enhanced GA and DWT for PCB identification	Elite Strategy, Genetic Algorithm, Discrete Wavelet Transform
[10]	2023	FFOA image fusion	Nonsubsampling contourlet transform (NSCT), contrast spatial frequency

[11]	2021	Multi-focus fusion for microscopic images	Bandpass filtering, Laplacian transform, thresholding, morphological ops, self-adjusting guided filter
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The proposed method incorporates multiple features such as texture, edge, and local variance, rather than using a single feature. It employs a genetic algorithm for adaptive optimization of feature weights through entropy maximization, to improve the selection of optimal fusion parameters and overall fusion quality.

3. Methodology

This study proposes a multi-focus image fusion approach that considers Genetic Algorithm (GA) optimization to achieve the selection of the most appropriate fusion weights that are used to increase the quality of the resulting fused image. This methodology consists of some stages, as shown in Figure 1 and algorithm 1. The complete workflow employed in the implementation is described below.

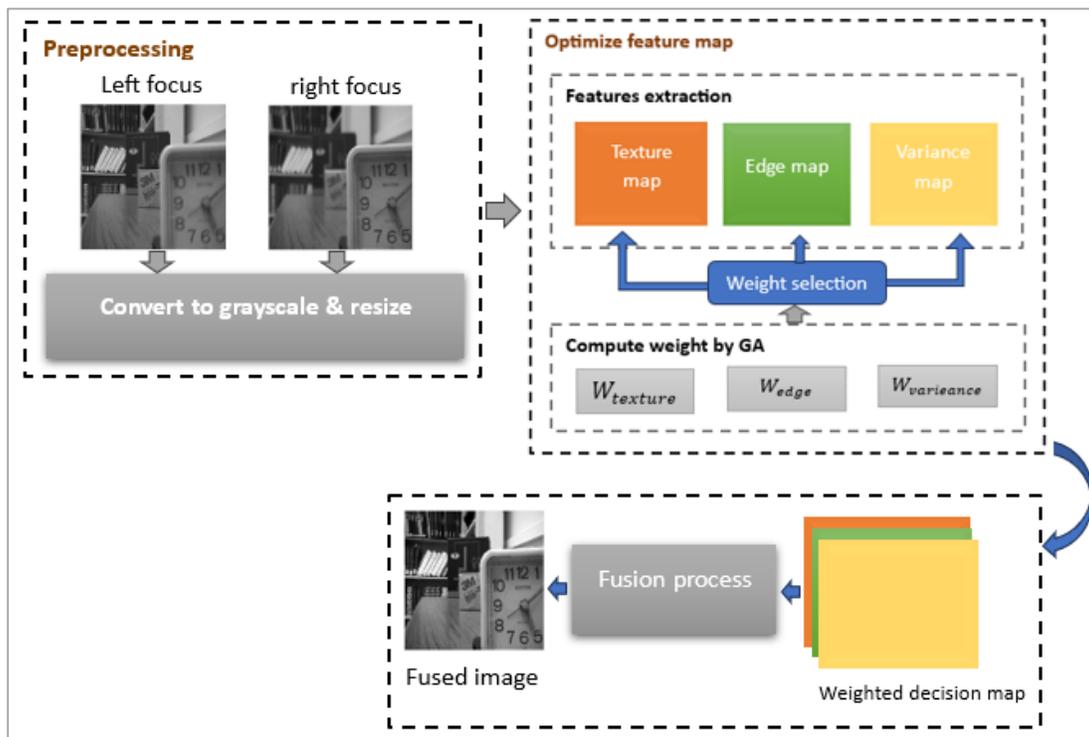


Figure (1): flowchart of the proposed fusion process

3.1: Read input images

The source images have been read, where two images with different focus levels of the same scene are loaded (left and right focuses).

3.2: preprocessing

Input images are converted to grayscale to ensure uniform intensity representation. And then, the images are resized to a dimension of 512×512 pixels to ensure spatial alignment and compatibility for subsequent fusion steps.

3.3: Feature Extraction and generate a combined features map

Each source image is initially examined to extract three feature maps, as demonstrated, for example Wine image in Figure 2. The texture map that is shown in Figure 2(a) identifies areas with fine features and textures by measuring local intensity variations using a standard deviation filter (STD) with a 3×3 block size [12], as explained in eq. (1,2). In order to retain significant edges in the fused image, the edge map that demonstrated in Figure 2(b) uses the Sobel operator [13] to identify structural boundaries. In order to provide more details regarding textured areas, the local variance map shown in Figure 2(c) assesses local intensity variations within 3*3 blocks of the image. A set of weights representing the relative importance of texture, edges, and local variation is then used to merge the feature maps and generate a weighted combined features map based on the fusion process

$$\mu_j = \frac{1}{N} \sum_{i=1}^N x_{ji} \quad (1)$$

$$\sigma_j = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_{ji} - \mu_j)^2} \quad (2)$$

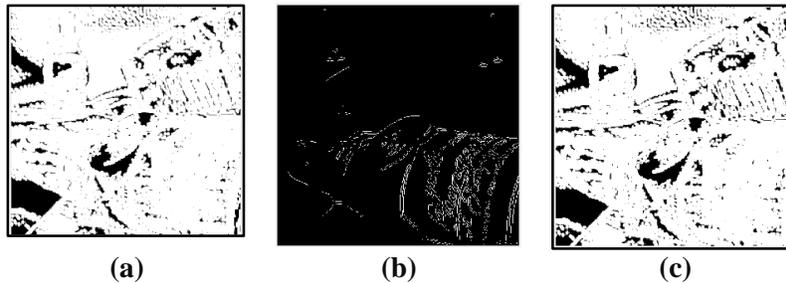


Figure (2): extracted features maps left focus (wine image), (a) texture, (b) edges, (c) variance

3.4: Fusion Optimization Using Genetic Algorithm

The GA algorithm [14, 15] is used in this stage to fuse two images using the combination of three feature maps: texture, edge, and variance, each assigned a weight reflecting its significance. It explores different weight combinations to calculate weighted maps and determines the strongest pixel values for the fused image. The quality of the fused image is optimized by employing the entropy measure, where a higher entropy value indicates better detail. The algorithm retains weights that yield the highest entropy over several generations, ultimately selecting the top three weights for optimal image fusion quality. The GA steps are explained in Algorithm 2 with a population size of 20 and max generation of 15.

3.5: Final Image Fusion

In this stage, a final image fusion is achieved based on two weighted decision maps (left focus, right focus), resulting from applying the evolutionary algorithm's optimal weights to the retrieved feature maps of the two source images. After that, a patch-based approach is used to create the final fused image. Each patch from the two images is assessed, and the patch with the highest mean value is chosen and added. This guarantees that the most focused and informative areas from both source images are preserved in the fused output. To explain this, we choose, for example, the two-decision map of the wine image as shown in Figure 3, emphasizing the selection of salient and detail-rich regions from two original images based on batch selection from the right and left focus images. A square shows the area with the highest quality feature, which will be selected for the final image to ensure focus on this region.

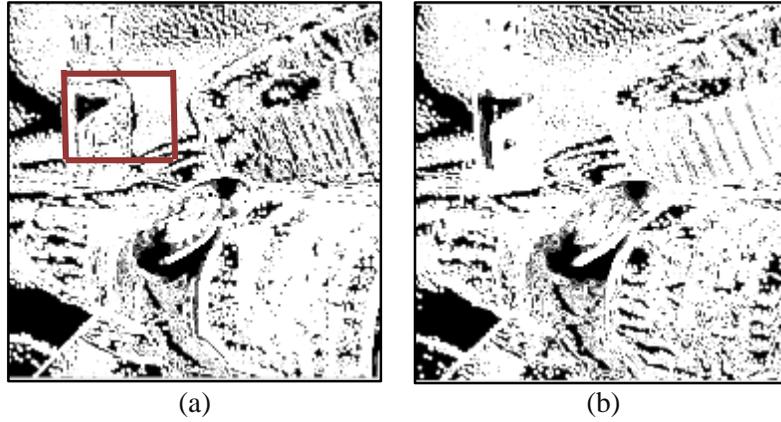


Figure (3): Patch-based fusion for wine image, (a) combination features map (right), (b) combination features map (left)

3.6: Enhancement of the Fused Image

At this stage, contrast enhancement is achieved by adjusting intensity values to improve the visual accuracy of the fused image, for easier recognition of targeted areas.

Algorithm 1: fused image optimization by GA

Input: Two source images: $img1$ and $img2$.

Output: fused image with optimal weights: w_{tex} , w_{edge} , w_{var}

Step 1: Compute feature maps for each image:

- Texture map using local standard deviation for two focuses (Left_text, Right_text)
- Edge map using the Sobel operator for two focuses (Left_edge, Right_edge)
- local variance map using sliding window variance for two focuses (Left_var, Right_var)

Step 2: Define the weight vector:

$w = [w_{tex}, w_{edge}, w_{var}]$
 where each weight $\in [0, 1]$.

Step 3: Define the fitness function:

For each candidate weight vector w by GA:

- Compute weighted feature maps:
 $combinedMap_{left} = w_{tex} \cdot Left_text + w_{edge} \cdot Left_edge + w_{var} \cdot Left_var$
 $combinedMap_{right} = w_{tex} \cdot Right_text + w_{edge} \cdot Right_edge + w_{var} \cdot Right_var$

Step 4: Perform patch-based fusion:

Divide the image into non-overlapping or sliding patches of size $P \times P$.

For each patch:

- Extract patch from both combined maps
- Compute the mean of each patch
- Select the patch from the image whose combined map has the higher mean:
 - If $mean(patch_1) > mean(patch_2)$: choose a patch from img_1
 - Else: choose a patch from img_2

Assemble all chosen patches into a temporary fused image $fused_temp$.

- Compute the **entropy** of the fused image to select the best weights (final fused):
 $E = entropy(fused_temp)$

Stage 5: Final Image Fusion

Construct final fused image

Algorithm 2: Genetic Algorithm for Optimal Feature Weight Selection
Input: multi-focus images $img1, img2$ feature maps including (Left_text, Right_text, Left_edge, Right_edge, Left_var, Right_var)
Output: Optimized feature weights $w_{tex}, w_{edge}, w_{var}$
Step 1: Initialize a population of candidate weight vectors ($w = [w_{tex}, w_{edge}, w_{var}]$) within the range $([0,1])$.
Step 2: For each individual in the population, generate a fused image using the corresponding feature weights.
Step 3: Evaluate the fitness of each individual using an entropy-based objective function.
Step 4: Select individuals with the highest fitness values as parents.
Step 5: Apply crossover to the selected parents to produce new offspring.
Step 6: Apply mutation to randomly modify some weights in the offspring to maintain diversity.
Step 7: Replace the old population with the new offspring population.
Step 8: Repeat Steps 2–7 until the maximum number of generations is reached.
Step 9: Select the best solution (x) from the final population.
Step 10: Extract the optimized weights ($w_{tex}, w_{edge}, w_{var}$) and use them for the final multi-focus image fusion.

4. Experimental Results and Discussion

To examine the efficiency of the proposed image fusion approach, some statistical metrics are used, such as standard deviation and mean intensity. Standard deviation is used to measure the contrast and detail, whereas mean intensity represents the brightness. As shown in Figures 4-6, the evaluation is achieved on a well-known standard image: a wine image (224x224 pixels), a disk (640x640 pixels), and a book (758x568 pixels). Tables (2-5) explain performance evaluations on two metrics standard deviation and mean.



Figure (4): explain left and right focus wine image, and fused image

Table (2): Performance evaluation for wine fused image

Wine image	Std	Mean
Left-focus (source)	67.4344	117.6591
Right-focus (source)	66.8530	117.6955
fused_final	69.3172	118.4333

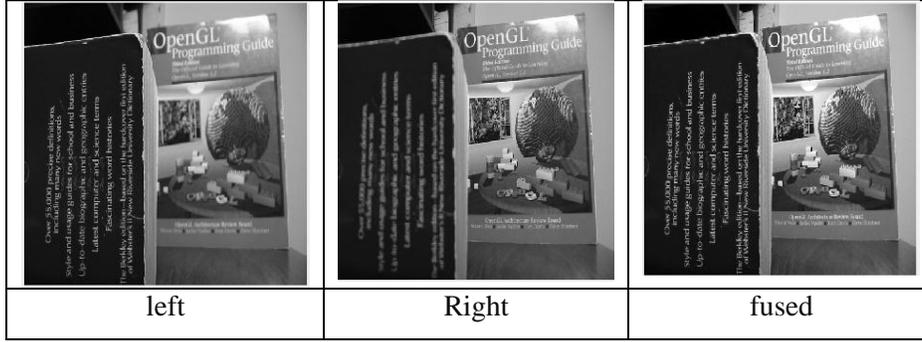


Figure (5): explain left and right focus book image, and the fused image

Table (3): Performance evaluation for book-fused image

Book image	Std	Mean
Left-focus (source)	59.0139	85.0133
Right-focus (source)	60.6950	84.8288
fused final	68.1366	90.7484



Figure (6): explain left and right focus disk image, and fused image

Table (4): Performance evaluation for disk-fused image

Book image	Std	Mean
Left-focus (source)	46.2232	98.9142
Right-focus (source)	43.5869	97.7508
fused final	62.8049	107.2628

The results shown in the previous tables indicate that the fused image maintains a balance of brightness and contrast, effectively combining information from the two source images. An increase in the standard deviation of the fused image demonstrates improved detail preservation, while the average value confirms good overall brightness preservation

Table (5): Performance evaluation based on SSIM, PSNR

Metric	Wine	Book	Disk
SSIM (fused, right)	0.5791	0.7546	0.4551
SSIM (fused, left)	0.5784	0.6347	0.6235
Average	0.5787	0.6946	0.5393
PSNR (fused, right)	22.0259	26.1657	19.2268
PSNR (fused, left)	21.4504	22.7136	21.4126
Average	21.7382	24.4396	20.3197

Table (6): performance evaluation for fused images in average

Fused image	Std	Mean	SSIM	PSNR
wine	69.3172	118.4333	0.5787	21.7382
Book	68.1366	90.7484	0.6946	24.4396
disk	62.8049	107.2628	0.5393	20.3197
Average	66.7529	105.4815	0.6042	22.1658

The fused image was tested based on the Structural Similarity Index (SSIM) with reference to both source images. The SSIM values as given to the wine image, for example are, in the case of the right-focused image, 0.578 and the left-focused image, 0.582, with an average of 0.580. These findings show that the fused image maintains the structural information on both sources in a proportionate way. The average similarity scores are expected since neither of the source images has complete focus in each and every area. On balance, the findings prove that the proposed patch-based GA fusion is an effective method of combining the well-centered regions of the two photographs.

The near PSNR of the right and left images indicates that the proposed fusion approach does not give preference to any of the images; therefore, the contribution of the two images is balanced. This is characteristic of image fusion in multi-focus, whereby the goal is to create a single image with a better visual quality of the multi-focused areas of various images.

5. Conclusion

The suggested multi-focus image fusion approach with Genetic Algorithm-optimized feature weighting successfully led to preserving texture, edges, and textures while optimizing useful content. As can be seen in the tables, the fused images display superior visual quality.

Acknowledgement

The authors thank the Department of Computer Science, College of Science, Mustansiriyah University, Baghdad-Iraq for supporting this present work.

Conflict of Interest: The authors declare that there are no conflicts of interest.

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