# A Modified Technique of Hybrid Multiobjective Genetic Algorithm for Image Fusion

Jyoti Kulkarni
Pimpri Chinchwad College of Engineering,
Savitribai Phule Pune University, India
jyoti.kulkarni@pccoepune.org

Rajankumar Bichkar
Vidya Pratishthan Kamalnayan Bajaj Institute of Engineering and Technology,
Savitribai Phule Pune University, India
principal.vpkbiet@vidyapratishthan.com

**Abstract:** *Sensors used in image acquisition. This sensor technology is going on upgrading as per user need or as per need of an application. Multiple sensors collect the information of their respective wavelength band. But one sensor is not sufficient to acquire the complete information of one scene. To gain the overall data of one part, it becomes essential to cartel the images from multiple sources. This is achieved through merging. It is the method of merging the data from dissimilar input sources to create a more informative image compared with an image from a single input source. These are multisensor photos e.g., panchromatic and multispectral images. The first image offers spatial records whereas the lateral image offers spectral data. Through visible inspections, the panchromatic photo is clearer than a multispectral photo however the grey shade image is. Articles are greater clear however now not recognized whereas multispectral picture displays one of a kind shades however performing distortion. So comparing the characteristics of these two images, the resultant image is greater explanatory than these enter images. Fusion is done using different transform methods as well as the Genetic Algorithm (GA). Comparing the results obtained by these methods, the output image by the GA is clearer. The feature of the resultant image is verified through parameters such as Root Mean Square Error (RMSE), peak signal to noise ratio, Mutual Information (MI), and Spatial Frequency (SF). In the subjective analysis, some transform techniques also giving exact fused images. The hybrid approach combines the transform technique and a GA is used for image fusion. This is again compared with GA results. The same performance parameters are used. And it is observed that the Hybrid Genetic Algorithm (HGA) is superior to the AG. Here the only RMSE parameter is considered under the fitness function of the GA so only this parameter is far better than the remaining parameters. If we consider all parameters in the fitness function of the GA then all parameters using a HGA will give better performance. This method is called a Hybrid Multiobjective Genetic Algorithm (HMOGA).*

**Keywords:** *Genetic algorithm, hybrid multiobjective genetic algorithm, image fusion*.

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## 1. Introduction

The fusion of images from the same source at a different time is called multitemporal image fusion. This type of image fusion is useful in change detection. The same material with different spectral phenomena gives the change in pixel value to find the changes. Change detection useful for land use, urban growth, forest dynamics and disaster management, etc., Numbers of image fusion techniques are available [6, 9, 23, 25, 29]. The image fusion strategies are spatial area and a frequency domain. The spatial area image fusion makes use of the images as it is i.e., they straight operate on pixels. In the frequency domain, the transform is used before image fusion. Spatial domain image fusion methods are averaging method, Principal Component Analysis (PCA), Intensity Hue Saturation (HIS) transform, High Pass Filtering (HPF), and Brovey Transform (BT). The drawback of spatial domain fusion is spectral poverty. Because of this, the transform domain fusion method is chosen. The transform domain approach makes use of different transforms such as Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), and Kekre transform. Among these, it is necessary to select the optimized technique or optimum fused image. As optimization is needed in the image fusion process, evolutionary algorithms can give the optimized output. The different evolutionary algorithms are Genetic Algorithm (GA), Genetic Programming (GP), Evolutionary Programming (EP), Learning Classifier System (LCS), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), Evolution Strategy (ES), Swarm Intelligence (SI), Tabu Search (TS), Cuckoo Search (CS), etc. The GA gives the solution for the optimization of hard problems quickly, reliably, and accurately [11, 24]. Each solution is separate and the set is the population. The objective characteristic rating is fitness. Higher objective function value solutions are replicated to allow more searches. Local search stages are mutation and crossover. Optimization proceeds in a sequence of generations. Two solutions that can be blended to create a new one is crossover. Fusion is done using these transform methods as well as the GA. Comparing the results obtained by these methods, it is concluded that the output produced by the GA is clearer. The superiority of the fused image is verified using performance parameters. In the subjective analysis, some transform techniques also giving a better output [3]. Then hybrid method i.e., combination of the transform technique and GA can be used for image fusion. This is again compared with GA results for the same performance parameters. And it is observed that the Hybrid Genetic Algorithm (HGA) is superior to the GA [14]. Here the only root means square error parameter is considered under the fitness function of the GA so only this parameter is way better than the remaining parameters.

When only one objective is involved in the problem, it is called single-objective optimization, but in most applications, more than one objective is required to be optimized. This is multi-objective optimization. The objective function values are compared to find the superiority of a solution in the single-objective optimization problem whereas, in the multi-objective optimization problem, the quality of the solution is determined by the dominance. As it may not be suitable to examine a fused image based on a single metric, the excellence of a fused image should be estimated by combining two or more metrics in a manner that overwhelms the limitations of the individual metric. By using the weighted sum method, the multi objectives are transformed into a single objective function [3]. Here, minimization problems with only two objectives are investigated. As discussed previously, in single objective method, the function used is Root Mean Square Error (RMSE). When the RMSE value is small, it indicates that the contents from input images are transferred into the fused image. Anyone parameter among the performance parameters Spatial Frequency (SF), Mutual Information (MI), Image Quality Index (IQI), and Average Gradient (AG), one can be added with RMSE in multiobjective function. Here SF is considered, as the SF gives the object's shape and size information. The performance of this method is observed by using different performance parameters.

This paper is organized into six sections. An introduction is the first section of the paper. After this, the next section will give knowledge about GA-based image fusion. Then, the fusion technique using a HGA is explained. The proposed technique and also the entire process are presented in the next section. Experimental results on three data sets are illustrated in the results and discussions part. Finally, conclusions are presented in the last section [15].

## 2. Image Fusion Using Genetic Algorithm

Simple GA works under the basic three operations like selection, genetic operation, and replacement. A Group of chromosomes can form a population that supplies the range of solutions. Initially, the population is chosen randomly and also the fitness of this solution is calculated using a fitness function. The fitter solution has more possibility to require a possibility in the second generation. Likewise, parents are selected in the selection step. Then crossover, as well as mutation operations, is performed on selected parents. The off springs are generated in this step. The parent i.e., old population is replaced by offspring [8, 16, 20, 28]. Image fusion can be done by searching appropriate block sizes from input images through genetic search and then fusing these clearer blocks [12]. The GA is also useful in image denoising. This is the preprocessing method for image fusion to remove the noise from input images [7, 21]. In remote sensing applications, a large number of filters is required to filter the data. The selection of filters is most important to achieve the required data information. This filter selection can be done by using a GA that is further used for optimal feature selection [17]. It is also possible to retrieve the image information using color features and texture features from the fused image using a GA [1, 13]. A GA is an unbiased optimization method to find the solution automatically. This increases the optimality with an increase in the generation or up to termination [15]. The GA is used for image fusion. In this, two images are selected from the dataset to perform image fusion. In a GA, create a preliminary population. This is created randomly with factors as size and number of bits. Population size is the number of chromosomes and the size of the chromosome given by the number of bits. For two input images, two populations are produced. The weight for the input image is nothing but the chromosome from the population is multiplied with the input image. These two new images are used for fusion. The fitness function is calculated for the fused image, will provide the fitness cost of every population. The same process is repeated for all populations. Next to the termination, the quantity of fitness values is the same as the population. Then the mediocre fitness is calculated. These fitness values are sorted in up order. Here, the first value is the best cost of the fitness function and the last value is the worst cost. For the probability of selection, roulette wheel selection can be used for the selection of parents. Then, with the help of crossover probability, two off springs can be formed using a single point or double point crossover. And with the mutation probability, two off springs are mutated and resulting chromosomes are inserted in the new population [3].

## 3. Image Fusion Using Hybrid Genetic Algorithm

In pixel-level GA-based image fusion, the input images are used by a genetic search to find an optimum weight for each input image. This is basic-level image fusion using a GA. To increase the quality of a fused image or for more optimization, the input image can be transformed by using any transform method before applying to a genetic search [2, 16, 18]. In image fusion under data assimilation through the model operator, a prediction image is the fused image after applying transform on input images. Through the observation operator, the observation image is the color composite of the image found by using IHS fusion. Now, these two images are used by the GA to find an optimized image [6, 10, 21]. Image fusion using a HGA is the modification in the previous method which will give the improved result.

The hybrid method can be formed by combining the SF which is working at the pixel level and the GA which is working at the feature level. Inputs are splits into segments. The segment size is decided by the GA. The corresponding blocks are compared to SF. The higher SF block is selected for fusion [12, 28]. Pixel level GA based, DWT based, and DWT-GA based fusion methods are explained in [16]. In the Pixel level GA-based method; the optimal weights are determined by the genetic search. The weight generated is less than 1 and then another weight is calculated such that the addition of two weights is 1. The fitness function used is the RMSE equation. The fused image is achieved by the sum of the multiplication of the respective weight with the image at the pixel level. The DWT based method is the simple WT method using the maximum fusion rule. The DWT-GA based method is the combination of two techniques. The input images are decomposed into wavelet coefficients. These coefficients are the inputs to the genetic search to find optimal weight. The input image is multiplied by this weight to form the fused image [16]. Instead of DWT, discrete wave packet decomposition can also be used with a GA for image fusion.

The HGA is the combination of transform technique and GA. Here, two input images i.e., panchromatic image and multispectral image are selected from the dataset for image fusion. Then, apply DCT on each band of input images separately. Now two transformed images are available. On these two input images, the GA is applied. The result obtained from this method is improved compared with the previous method. Instead of DCT, other transform methods can also be used such as DWT and Kekre's WT [14].

## 4. Image Fusion Using Hybrid Multiobjective Genetic Algorithm (HMOGA)

A Pareto Optimal (PO) set is a set of non-dominated solutions. Among the set of PO solutions, there are variations in the value of objectives from one solution to other solution. It may happen that one solution is giving best value of one objective whereas other solution is giving worst for the same. For single solutions, PO solution sets are frequently desired [12, 27]. Pareto dominance and Pareto front used to find near optimal solution but simultaneous searching can be done by using multiobjective optimization to find optimal solution [5, 19, 26]. Thus multiobjective evolutionary algorithm is the best solution for multiple feature extraction. In this, for different features, different chromosomes with fitness function can be used [4, 22]. The Hybrid Multiobjective Genetic Algorithm (HMOGA) is the HGA for multiple parameters. The different performance parameters can be used in fitness function of GA as given in Figure 1.

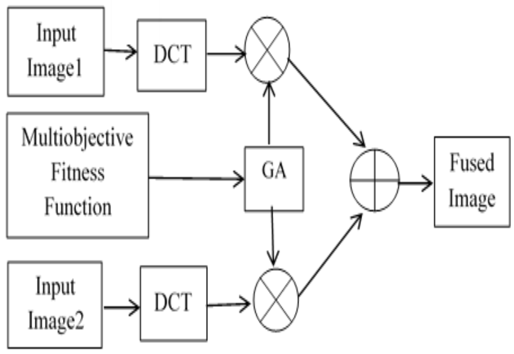



Figure 1. Image fusion using HMOGA.

The algorithm for image fusion by HMOGA is as follows:

1. Selecting two images from given dataset.
2. Apply the required transform method on these input images separately. Two transformed images are available.
3. Generate preliminary population. It is created randomly with factors as size and number of bits. Initially take pop size as 50 and size of chromosomes as 16 bits.
4. Randomly generate the weight used for each image. Then multiply this weight with the input image. And fuse these images.
5. Apply the fitness function to the fused image. This contains the performance parameters as RMSE, MI, and SF. This is the fitness of the population.
6. Repeat steps 3 to 5 for all populations. Finally, the numbers of fitness values are equivalent to the number of populations. The average fitness of these populations is calculated.
7. The values are sorted in descending order. As larger cost is the best cost, this is the first value whereas the worst cost is the last value.
8. The selection probability is calculated for the parent selection using the roulette wheel selection method.
9. Now by the crossover probability forming two offspring using double point crossover.
10. Calculate the mutation probability. The two off springs are mutated and the resulting chromosome is placed in the new population.
11. The current population is replaced by the new one.
12. Steps 2 to 11 are repeated for all generations.

The fitness function for this algorithm is:

$$f(x) = min\{\left(\frac{1}{SF}\right), Rmse\} \quad (1)$$

Where RMSE is the root mean squared error and SF is SF. These parameters are defined as given below.

- Root Mean Square Error: it is the amount of accuracy. It finds the change between the original and fused image. As a result, RMSE is calculated as:

$$\text{Rmse} = \sqrt{\frac{1}{\text{M} * \text{N}} \sum_{i=1}^{M} \sum_{j=1}^{N} (\text{Im}(i,j) - \text{Imf}(i,j))^2} \qquad (2)$$

Where *Im* is the standard image, *Imf* is the fused image, *MxN* is the size of the image.

- Spatial Frequency: this provides the spatial information of an image concerning the high frequency and low-frequency domain. It is calculated as

$$\text{SF} = \sqrt{\text{CF}^2 + \text{RF}^2} \qquad (3)$$

Where *CF* and *RF* are the column and row frequency of an image respectively.

## 5. Results and Discussions

The acts of the image fusion technique are assessed by RMSE, MI, IQI, and SF. Setting the genetic operators as per Table 1, and observed the performance. The input images are used for testing and observed the output. The types of inputs are multisensory Red Green Blue (RGB) and Gray images, multisensor medical images, and multifocus RGB images. These images are taken from the standard dataset. This is assumed that images are properly registered. Simulation is carried out using the Image processing toolbox in Matlab on Intel (R) Celeron (R) 1.50 GHz Central Processing Unit (CPU) processor. Analysis of the output images is done in three steps: through visual inspection, through different performance parameters, and from histogram analysis.

Table 1. Genetic operators.

| **Operator** | **Value** |
|---|---|
| Iterations | 100 |
| Chromosome size | 50 |
| Mutation rate | 0.05 |
| Bits in chromosome | 8/16 |
| Crossover type | Double point |

The primary step of analysis is the visual inspection. Figures 2, 3, 4, 5, 6, 7, 8, and 9 shows the input images and output images due to the above-described methods. Figure 2-a) is the panchromatic and (b) is the multispectral input. Comparing (c, d, and e), (c) and (e) are almost the same whereas (d) which is the output of HGA, is giving more spectral information. Figure 4-a) and (b) are multifocus images where the focus is on a different part of the scene. Observing the output images, here also output due to HGA is superior to the rest of the methods. Medical input images are given in Figure 4-a) and (b). In this test set, the output due to GA is clearer than HGA.

a) Input image 1. b) Input image 2. c) GA output. d) HGA output. e) HMOGA output.

Figure 2. Image fusion for multisensor input images test set 1.

a) Input image 1. b) Input image 2. c) GA output. d) HGA output. e) HMOGA output.

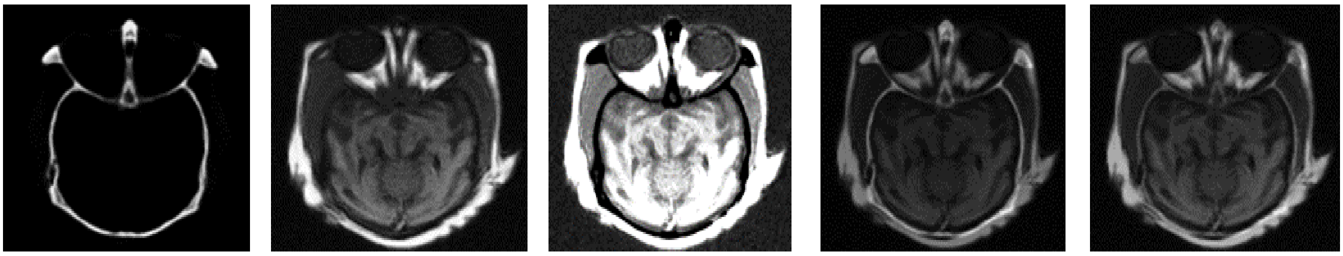
Figure 3. Image fusion for multisensor input images test set 2.


a) Input image 1. b) Input image 2. c) GA output. d) HGA output. e) HMOGA output.

Figure 4. Image fusion for multifocus input images test set 1.

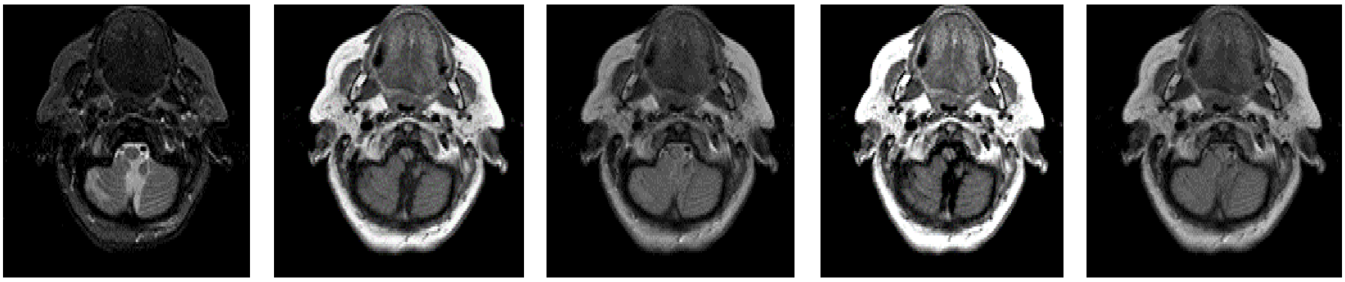

a) Input image 1. b) Input image 2. c) GA output. d) HGA output. e) HMOGA output.

Figure 5. Image fusion for multifocus input images test set 2.



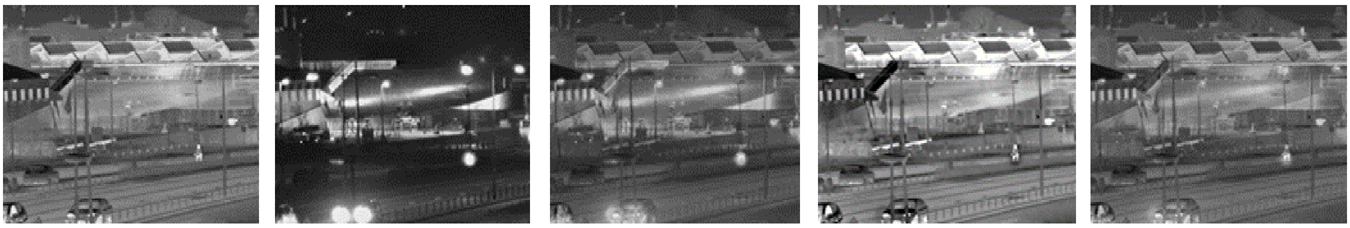
a) Input image 1. b) Input image 2. c) GA output. d) HGA output. e) HMOGA output.

Figure 6. Image fusion for multisensor medical input images test set 1.



a) Input image 1. b) Input image 2. c) GA output. d) HGA output. e) HMOGA output.

Figure 7. Image fusion for multisensor medical input images test set 2.



a) Input image 1. b) Input Image 2. c) GA output. d) HGA output. e) HMOGA output.

Figure 8. Image fusion for multisensor night vision input images test set 1.

a) Input image 1. b) Input image 2. c) GA output. d) HGA output. e) HMOGA output.

Figure 9. Image fusion for multisensor night vision input images test set 2.

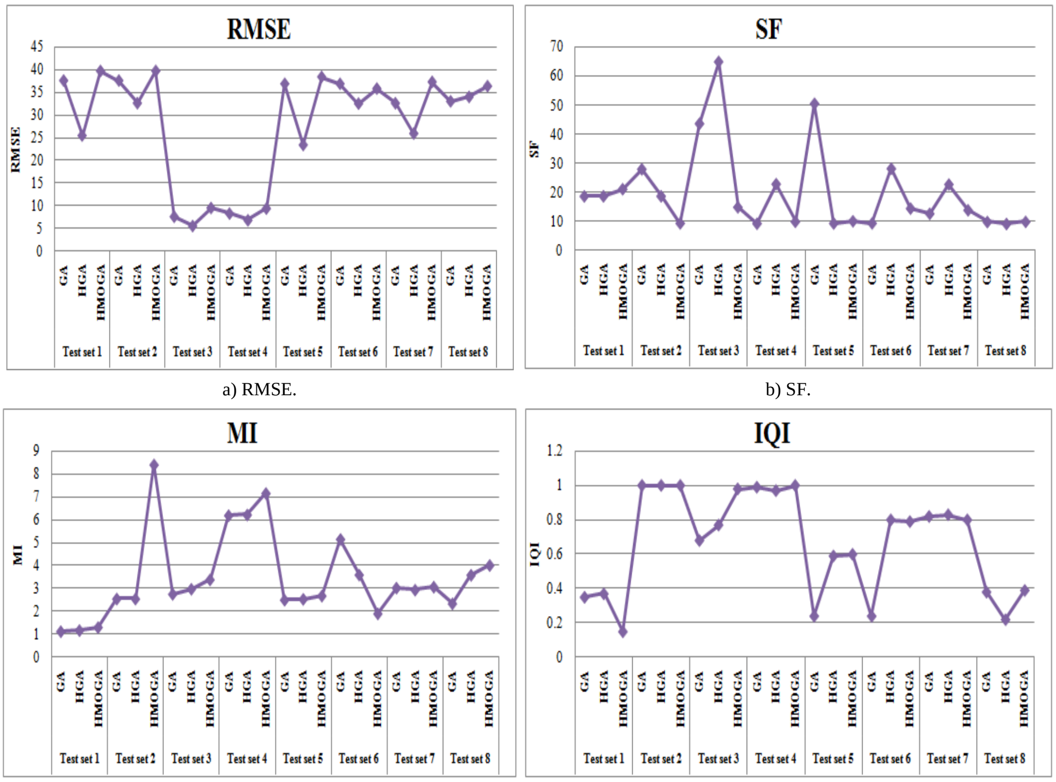
Another way of analysis of output generated by different methods is through performance parameters. Tables 2 and 3 are the detailed representation of these parameters. Figure 10 is the graphical representation of some parameters such as RMSE, SF, MI, and IQI. The RMSE behavior in GA and HMOGA is almost the same but in HGA, it is better than GA and HMOGA. But by observing the rest of the parameters i.e., SF, MI, and IQI, the performance of HMOGA is better than HGA which is better than GA.

Table 2. Performance parameters of output image using GA, HGA, and HMOGA for different image groups.

| Quality indices | Multisensor images _Test set 1 | | | Multifocus images _Test set 1 | | | Multisensor medical images _Test set 1 | | | Multisensor night vision images _Test set 1 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | GA | HGA | HMOGA | GA | HGA | HMOGA | GA | HGA | HMOGA | GA | HGA | HMOGA |
| **Mean** | 120 | 117.6 | 133.9 | 156.2 | 158.3 | 156.9 | 137.8 | 30.8 | 39.9 | 92.39 | 87.15 | 93.50 |
| **Entropy** | 7.22 | 7.24 | 7.22 | 7.59 | 7.48 | 7.40 | 5.06 | 5.88 | 5.99 | 6.94 | 6.93 | 6.94 |
| **Var** | 1656 | 1680 | 1796 | 5511 | 8306 | 4521 | 1028 | 1113 | 1646 | 1069.80 | 1159.92 | 1061.86 |
| **Stddev** | 40.6 | 40.98 | 42.38 | 74.24 | 91.14 | 67.24 | 175.94 | 33.37 | 40.57 | 32.71 | 34.06 | 32.59 |
| **RMSE** | 37.6 | 25.50 | 39.70 | 7.64 | 5.60 | 9.57 | 36.88 | 23.42 | 38.42 | 32.61 | 25.94 | 37.30 |
| **PSNR** | 37.2 | 37.12 | 35.53 | 41.27 | 30.81 | 65.35 | 5.35 | 37.92 | 36.41 | 21.64 | 26.65 | 36.71 |
| **SF** | 18.7 | 18.72 | 21.17 | 43.60 | 64.83 | 14.94 | 50.47 | 9.41 | 10.15 | 12.74 | 22.78 | 13.92 |
| **MI** | 1.12 | 1.17 | 1.30 | 2.76 | 2.98 | 3.39 | 2.50 | 2.54 | 2.68 | 3.03 | 2.94 | 3.07 |
| **IQI** | 0.35 | 0.37 | 0.15 | 0.68 | 0.77 | 0.98 | 0.24 | 0.59 | 0.60 | 0.82 | 0.83 | 0.80 |
| **AG** | 76.0 | 74.45 | 88.41 | 110.5 | 143.62 | 50.77 | 97.84 | 37.90 | 43.65 | 5.16 | 4.95 | 5.22 |

Table 3. Performance parameters of output image using GA, HGA, and HMOGA for different image groups.

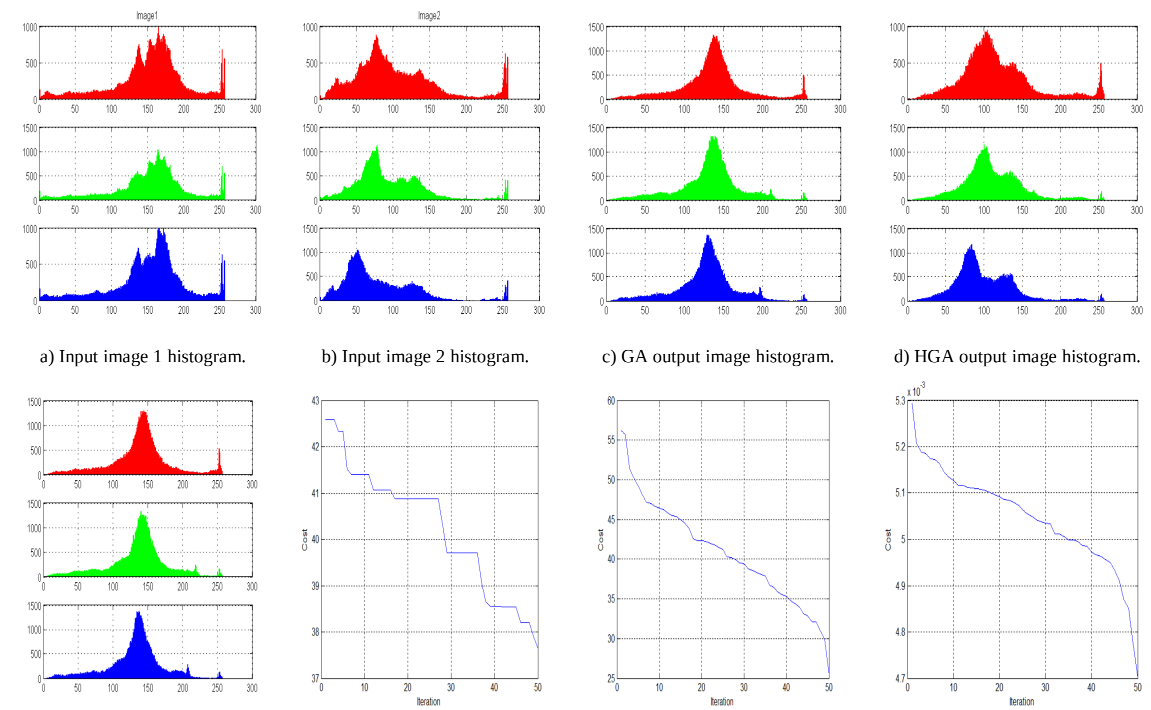
| Quality indices | Multisensor images _Test set 2 | | | Multifocus images _Test set 2 | | | Multisensor medical images _Test set 2 | | | Multisensor night vision images _Test set 2 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | GA | HGA | HMOGA | GA | HGA | HMOGA | GA | HGA | HMOGA | GA | HGA | HMOGA |
| **Mean** | 108 | 108.18 | 111.64 | 67.57 | 67.40 | 67.49 | 33.45 | 37.54 | 46.33 | 43.17 | 62.09 | 66.29 |
| **Entropy** | 7.79 | 7.79 | 7.89 | 6.08 | 6.08 | 6.08 | 5.92 | 5.07 | 5.15 | 5.59 | 6.21 | 6.33 |
| **Var** | 3205 | 3204.2 | 4019.3 | 3706 | 3698.39 | 3700.40 | 1223.2 | 2005 | 3209.8 | 413.51 | 542.11 | 627.69 |
| **Stddev** | 56.6 | 56.61 | 63.40 | 60.88 | 60.81 | 60.83 | 34.97 | 44.78 | 56.66 | 20.33 | 23.28 | 25.05 |
| **RMSE** | 37.6 | 32.63 | 39.71 | 8.33 | 6.86 | 9.44 | 36.88 | 32.52 | 35.82 | 33.02 | 34.00 | 36.36 |
| **PSNR** | 37.2 | 37.14 | 9.58 | 65.73 | 44.54 | 65.08 | 5.35 | 26.20 | 38.78 | 38.93 | 39.01 | 38.08 |
| **SF** | 28.0 | 18.73 | 9.44 | 9.33 | 22.89 | 9.97 | 9.43 | 28.17 | 14.50 | 9.90 | 9.23 | 9.95 |
| **MI** | 2.55 | 2.55 | 8.42 | 6.20 | 6.23 | 7.17 | 5.16 | 3.60 | 1.90 | 2.34 | 3.59 | 4.02 |
| **IQI** | 1.00 | 1.00 | 1.00 | 0.99 | 0.97 | 1.00 | 0.24 | 0.80 | 0.79 | 0.38 | 0.22 | 0.39 |
| **AG** | 13.4 | 13.37 | 37.30 | 2.31 | 2.28 | 2.33 | 3.59 | 4.56 | 4.49 | 2.81 | 3.60 | 3.85 |




a) RMSE. b) SF.

c) MI. d) IQI.

Figure 10. Performance parameters of the fused image using HMOGA.




a) Input image 1 histogram. b) Input image 2 histogram. c) GA output image histogram. d) HGA output image histogram.

e) HMOGA output image histogram. f) GA output image fitness function behavior. g) HGA output image fitness function behavior. h) HMOGA output image fitness function behavior.

Figure 11. Histogram representation and fitness function behavior of output images due to GA, HGA, HMOGA.

The third method of analysis is through histogram representation. The histogram gives the statistics of the total number of pixels in a specific value region. The above histogram is of multisensor satellite images where Figure 11-a) is the histogram of panchromatic and (b) is of multispectral. Thus comparing the histograms of output images generated due to GA, HGA, and HMOGA given in Figure 11-c), (d), and (e) respectively, the spectrum band in (d) is good as compared with the remaining pictures.

## 6. Conclusions

Image fusion is a powerful technique to extract important data from input images. However, image fusion using existing methods such as spatial domain or transform domain were not giving optimized results. Optimization can be accomplished through evolutionary approaches. A GA is one of the important tools. This is used with different transform techniques for image fusion. As the GA is well proven for the optimized result, it is combined with transform techniques to increase the performance of the method. This is a HGA method for image fusion. This is giving optimized results for a single performance parameter. Optimization of multiple performance parameters is done by using a HMOGA. In this, multiple parameters such as RMSE, SF, MI, and IQI are optimized. The fitness function is designed using these parameters. And from Tables 2 and 3, our proposed method is giving better results.

## References

[1] Aparna K., "Retrieval of Digital Images Based on Multi-Feature Similarity Using Genetic Algorithm," *International Journal of Engineering Research and Applications*, vol. 3, no. 4, pp. 1486-1499, 2013. https://www.ijera.com/papers/Vol3_issue4/IC3414861499.pdf

[2] Arif M. and Wang G., "Fast Curvelet Transform through Genetic Algorithm for Multimodal Medical Image Fusion," *Soft Computing*, vol. 24, pp. 1815-1836, 2020. DOI:10.1007/s00500-019-04011-5

[3] Aslants V. and Kurban R., "Extending Depth of Field by Image Fusion Using Multi-objective Genetic Algorithm," *in Proceedings of the 7th IEEE Conference on Industrial Informatics*, Cardiff, pp. 331-336, 2009. DOI: 10.1109/INDIN.2009.5195826

[4] Bahl M., Lehana P., and Kumari S., "Image Brightness Enhacement of Natural and Unnatural Images Using Continuous Genetic Algorithm," *International Journal of Advanced Research in Computer Science and Software Engineering*, vol. 3, no. 9, pp. 948-959, 2013.

[5] Bhatt H., Bharadwaj S., Singh R., and Vatsa M., "Recognizing Surgically Altered Face Images Using Multiobjective Evolutionary Algorithm," *IEEE Transactions on Information Forensics and Security*, vol. 8, no. 1, pp. 89-100, 2013. DOI: 10.1109/TIFS.2012.2223684

[6] Dey T., "A Survey on Different Fusion Techniques of Visual and Thermal Images for Human Face Recognition," *International Journal of Electronics Communication and Computer Engineering*, vol. 4, no. 6, pp. 10-14, 2013. https://ijecce.com/Download/conference/NCRTCST-2/03NCRTCST-1306.pdf

[7] Farid M., Mahmood A., and Al-Maadeed S., "Multi-Focus Image Fusion Using Content Adaptive Blurring," *Information Fusion*, pp. 1-17, 2018. DOI: 10.1016/j.inffus.2018.01.009

[8] Gattim N., Rajesh V., Partheepam R., Karunakaran S., and Reddy K., "Multimodal Image Fusion Using Curvelet and Genetic Algorithm," *Journal of Scientific and Industrial Research*, vol. 76, no. 11, pp. 694-696, 2017. https://nopr.niscpr.res.in/bitstream/123456789/43038/1/JSIR%2076(11)%20694-696.pdf

[9] Han X., Lv T., Song X., Nie T., Liang H., He B., and Kuijper A., "An Adaptive Two-Scale Image Fusion of Visible and Infrared Images," *IEEE Access*, vol. 7, pp. 56341-56352, 2019. DOI: 10.1109/ACCESS.2019.2913289

[10] Jeong W., Han B., Yang H., and Moon Y., "Real-Time Visible-Infrared Image Fusion Using Multi-Guided Filter," *KSII Transactions on Internet and Information Systems*, vol. 13, no. 6, pp. 3092-3107, 2019. DOI: 10.3837/tiis.2019.06.018

[11] Kaur R. and Kaur S., "An Approach for Image Fusion Using PCA and Genetic Algorithm," *International Journal of Computer Applications*, vol. 145, no. 6, pp. 54-59, 2016. DOI: 10.5120/ijca2016910816

[12] Kong J., Zheng K., Zhang J., and Feng X., "Multifocus Image Fusion Using Spatial Frequency and Genetic Algorithm," *International Journal of Computer Science and Network Security*, vol. 8, no. 2, pp. 220-224, 2008. https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=78cf087c30e324a3222215b5a72b8ec7ce00b4d3

[13] Kulkarni J. and Bichkar R., "Optimization in Image Fusion Using Genetic Algorithm," *International Journal on Image, Graphics and Signal Processing*, vol. 8, pp. 50-59, 2019. DOI: 10.5815/ijigsp.2019.08.05

[14] Kulkarni J., "Genetic Algorithm Approach for Image Fusion: A Simple Method and Block Method," *International Journal of Innovative Technology and Exploring Engineering*, vol. 11 no. 6, pp. 16-21, 2022. DOI: 10.35940/ijitee.F9895.0511622

[15] Kulkarni J. and Bichkar R., "Image Fusion using Hybrid Genetic Algorithm," *International Journal on Emerging Technologies*, vol. 11, no. 3, pp. 442-447, 2020. https://www.researchtrend.net/ijet/pdf/Image%20Fusion%20using%20Hybrid%20Genetic%20Algorithm%20%20Jyoti%20%20Sj4.pdf

[16] Lacewell C., Gebril M., Buaba R., and Homaifar A., "Optimization of Image Fusion Using Genetic Algorithms and Discrete Wavelet Transform," *in Proceedings of the IEEE National Aerospace and Electronics Conference*, Dayton, pp. 116-121, 2010. DOI: 10.1109/NAECON.2010.5712933

[17] Li J. and Zhang F., "A Novel Approach to Adaptive Image Fusion Using Multiobjective Evolutionary Algorithm," *International Journal of Digital Content Technology and its Applications*, vol. 7, no. 8, pp. 301-309, 2013.

[18] Luan J., Yao Z., Zhao F., and Song X., "A Novel Method to Solve Supplier Selection Problem: Hybrid Algorithm of Genetic Algorithm and Ant Colony Optimization," *Mathematics and Computers in Simulation*, vol. 156, pp. 294-309, 2019. DOI: 10.1016/j.matcom.2018.08.011

[19] Patil C., Kolte M., Chatur P., and Chaudhari D., "Optimum Features Selection by Fusion Using Genetic Algorithm in CBIR," *International Journal on Image, Graphics and Signal Processing*, vol. 7, no. 1, pp. 25-34, 2015. DOI:10.5815/ijigsp.2015.01.04

[20] Paulinas M. and Ušinskas A., "A Survey of Genetic Algorithms Applications for Image Enhancement and Segmentation," *Information Technology and Control*, vol. 36, no. 3, pp. 278-284, 2007. https://www.itc.ktu.lt/index.php/ITC/article/view/11886

[21] Pedergnana M., Marpu P., Mura M., Benediktsson J., and Bruzzone L., "A Novel Technique for Optimal Feature Selection in Attribute Profiles Based on Genetic Algorithms," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 51, no. 6, pp. 3514-3528, 2013. DOI: 10.1109/TGRS.2012.2224874

[22] Shabu J. and Jayakumar C., "Multimodal Image Fusion Using an Evolutionary-Based Algorithm for Brain Tumor Detection," *Biomedical Research*, vol. 29, no. 14, pp. 2932-2937, 2018. DOI: 10.4066/biomedicalresearch.29-18-799

[23] Shen D., Liu J., Xiao Z., Yang J., and Xiao L., "A Twice Optimizing Net with Matrix Decomposition for Hyperspectral and Multispectral Image Fusion," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 13, pp. 4095-4110, 2020. DOI: 10.1109/JSTARS.2020.3009250

[24] Sindian S., Samhat A., Crussière M., Hélard J., and Khalil A., "Mesh HDR WPAN Resource Allocation Optimization Approaches," *The International Arab Journal of Information Technology*, vol. 16, no. 3A, pp. 525-532, 2019. https://www.iajit.org/portal/PDF/Special%20Issue%202019,%20No.%203A/18598.pdf

[25] Taher G., Wahed M., Taweal G., and Fouad A., "Image Fusion Approach with Noise Reduction Using Genetic Algorithm," *International Journal of Advanced Computer Science and Applications*, vol. 4, no. 11, pp. 10-16, 2013. DOI : 10.14569/IJACSA.2013.041103

[26] Wang S. and Luo X., "Multi-objective Optimization and Gray Association for Multi-Focus Image Fusion," *Journal of Algorithms and Computational Technology*, vol. 10, no. 2, pp. 90-98, 2016. DOI: 10.1177/1748301816640712

[27] Xia J., Lu Y., and Tan L., "Research of Multimodal Medical Image Fusion Based on Parameter-Adaptive Pulse-Coupled Neural Network and Convolutional Sparse Representation," *Hindawi Computational and Mathematical Methods in Medicine*, vol. 2020, pp. 1-13, 2020. DOI: 10.1155/2020/3290136

[28] Zhang J., Feng X., Song B., Li M., and Lu Y., "Multifocus Image Fusion Using Quality Assessment of Spatial Domain and Genetic Algorithm," *in Proceedings of the IEEE Conference on Human System Interactions*, Krakow, pp. 71-75, 2008. DOI: 10.1109/HSI.2008.4581411

[29] Zhao Y., Qiao Y., Zhang C., Zhao Y., and Wu H., "Terahertz/Visible Dual-band Image Fusion Based on Hybrid Principal Component Analysis," *Journal of Physics: Conference Series*, vol. 1187, no. 4, pp. 1-5, 2019. DOI: 10.1088/1742-6596/1187/4/042096

**Jyoti Kulkarni** is working as Associate Professor in Pimpri Chinchwad College of Engineering. Her research interests include image fusion and optimization techniques. Her teaching interest includes data structures and algorithms, object oriented programming, design and analysis of algorithms.

**Rajankumar Bichkar** is working as Principal in Vidya Pratishthan's Kamalnayan Bajaj Institute of Engineering and Technology. His research interest includes genetic algorithm. He had published more than 56 research papers in international journals and conference.