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Genetic Algorithm Approach for Image Fusion: A Simple Method and Block Method

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Abstract: ***The sensors available nowadays are not generating images of all objects in a scene with the same clarity at various distances. The progress in sensor technology improved the quality of images over recent years. However, the target data generated by a single image is limited. For merging information from multiple input images, image fusion is used. The basis of image fusion is on the image acquisition as well as on the level of processing and under this many image fusion techniques are available. Several input image acquisition techniques are available such as multisensor, multifocus, and multitemporal. Also, image fusion is performed in four different stages. These levels are the level of the signal, pixel level, level of feature, and level of decision-making. Further, the fusion methods are divided into two domains i.e spatial and frequency domains. The fusion in spatial domain images uses inputs directly to work on pixels, while the transition refers to frequency domain image fusion on input images before fusion. The limitation of spatial domain image fusion is spectral degradation. To overcome this limitation, the fusion of transform domain images is preferred which uses several transforms. The results generated by transform methods are superior to spatial domain methods. But there is a scope to improve the results or to find the optimized results. Optimization can be achieved by using evolutionary approaches. The evolutionary computation approach is an effective way of finding the required solution for a complex problem. An evolutionary algorithm is a guided random search used for optimization. The biological model of evolution and natural selection inspires it. The different types of evolutionary computing algorithms include Genetic algorithm, Genetic Programming, Evolutionary programming, Learning Classifier System, Ant Colony Optimization, Artificial Bee Colony Optimization, Particle Swarm Optimization, Evolution strategy, Swarm intelligence, Tabu Search, Cuckoo Search, etc. Three genetic algorithm-based image fusion techniques are proposed: a genetic algorithm with one population, a genetic algorithm with separate populations, and a block method. In the block method, an array of numbers in one chromosome is generated. The result obtained by the proposed techniques are compared with existing methods and observed that the results are improved. The graphical representation of performance parameters reflects that the block method is better.***

Keywords**: *Optimization, Simple integer one population, Simple integer separate population, Block Method***

I. INTRODUCTION

The Genetic Algorithm (GA) is an advanced algorithm based on directed random search methods. GA is designed to estimate evolutionary methods by adopting the existence of the most appropriate theory. It is based on the theory of selective breeding, where the genome is taken as a stream of bits. The fitness feature assesses each individual from the population. Among these, the next generation will include high fitness individuals, and low fitness individuals are generally overlooked. Roulette wheel selection, rank-based selection, tournament selection, truncation selection, steady-state selection, elitism, and stochastic universal selection are some selection strategies. Many applications use GA in optimization such as function optimization, image processing, robotics, facial recognition, parameter optimization, and multi-objective optimization [3].

In Zhang et al. [2], the multi-focus image fusion is clarified using an evolutionary algorithm and quality assessment. The images are partitioned into segments. The segment size is produced by the GA. These segments are compared for spatial frequency. The higher spatial frequency segment is used in the resultant image. Gupta et al. [11] proposed wave packet image fusion dependent on a genetic algorithm. The input images are broken down into packets using a discrete wavelet packet transform. The respective coefficient is compared based on entropy to form a resultant image. The inverse transform is taken. This image is given to a genetic algorithm for denoising by using peak signal to noise ratio as the fitness function. Input images are broken down into two subbands using the wavelet transform as low-frequency subbands and high-frequency subbands. The use of a genetic algorithm selects the mean of low and high-frequency subbands for optimal data and then the inverse wavelet transform is applied to find thefused image. In Lacewell et al. [4], the genetic algorithm uses a discrete wavelet to combine inputs at the pixel level to transfer the details. Performance is tested by different quality metrics. The GA based IF is an incremental method. GA runs until the desired output is achieved by a fused image or the maximum number of iterations is performed. GA is often used to provide an optimal solution for a longer time [5]. The magnetic resonance image for the feature elements is taken into account in medical applications. By using the genetic algorithm, the optimized feature vector is also chosen[6]. Kong *et al*. [1], and Zhang *et al*. [2] proposed spatial frequency and genetic algorithm-based multifocus image fusion at pixel and feature levels. In the proposed technique, the inputs are broken down into blocks, and then the corresponding block with higher spatial frequency is chosen to get the final image. The suitable size of the block is decided by a genetic algorithm. Aslantas*et al*. [3] proposed a spatial domain IF method using a multiobjective genetic algorithm. The input images are separated into blocks that do not overlap. The respective blocks of input images are compared for spatial frequency.

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The higher spatial frequency blocks form the fused image. The fitness of the fused image is calculated by multiobjective evaluation. Here the size of blocks is decided by a multiobjective genetic algorithm.

Lacewell*et al.* [4] investigated a new technique using a genetic algorithm and DWT. The technique calculatesa separate 1 x 40 attribute matrix of input images. After wavelet decomposition, the feature vector of central moments of wavelet edges and another feature vector focused on the mean and standard deviation of magnitude of wavelet coefficients are available. These two feature vectors are given to a genetic algorithm to find optimal weights for inputs for fusion. Siddiqui *et al.* [9, 11] proposed multifocus image fusion using classification. The inputs are splits into blocks. The block feature vector is given to the feed-forward neural network. This trained network is used to fuse any pair of input images. The optimum block size is selected by GA.

Uttam Kumar *et al.* [6] presented the analysis of ten different image fusion techniques. These techniques are Component Substitution, Local Mean and Variance Matching, Modified IHS, Fast Fourier transformed-enhanced IHS, Generalized Laplacian Pyramid, Local Regression, Smoothing Filter, Sparkle, SVHC, and Synthetic Variable Ratio. Saeedi*et al.*[7] explaineda technique using fuzzy logic and a population-based optimization method. DTDWT followed by a fuzzy approach for high-frequency factors and particle swarm optimization for low-frequency factors is used for infrared and visible inputs.

A technique for image fusion by the multiobjective evolutionary algorithm is suggested by Junfeng *et al.*[8]. To break down the inputs into low and high-frequency coefficients, non-sampled contourlet transformation is used. Fusion rule selects proper low frequency and high-frequency coefficient forming an image. Applying inverse nonsubsampled contourlet transform gives the fused image. Zhao*et al.*[9] analyzed multifocus image fusion based on the neighbor distance where it is suitable to measure the clarity of pixel for image fusion. Huang *et al.*[10] presented sparse matrix factorization for spatial and spectral image fusion. In this, the model is trained from a high spectral resolution image, and then high spatial and spectral data is predicted from the input images. Gupta *et al.*[11] proposed a technique based on wave packets combined with a genetic algorithm. The input images are divided into packets using discrete wavelet packet transform. The respective coefficient is compared based on entropy to form the resultant image and then inverse transform is applied. This image is given to a genetic algorithm for denoising by using peak signal to noise ratio as the fitness function.

Saleh*et al.*[12] presented iris and signature multibiometrics system for particular identification using ant colony optimization method. Feature extraction and classification are done by using contourlet transform and ant colony optimization respectively. Liu *et al.*[13] explained the quaternion wavelet transform and normalized cut method. The texture data is given by quaternion wavelet transform whereas detection error is removed by normalized cut. Cao *et al.* [14] explained the multifocus image fusion technique in the discrete transform domain. The input images are decoded into blocks of size 8 x 8. The spatial frequency of each block is calculated. The decision map is used to record the feature according to the selection rule. Consistency verification is used to refine the decision map. The fused image is obtained from this map.

Wang *et al.*[15] presented multiobjective optimization and gray association. The Shearlet transform is used to decompose the image into low frequency and high-frequency coefficients. The low-frequency coefficients are selected based onthe weighted average fusion rule and the region-based fusion rule is applied for high-frequency coefficients. The particle swarm optimization and gray relation analysis are used to find the optimum weight.

Kaur*et al.* [16] proposed a hybrid model for using PCA and genetic algorithm where initially images are fused using PCA technique and then the genetic algorithm is used to optimize the fused image. Degadwala*et al.* [17] explained the image fusion using hybrid transformation where two transform techniques i.e DWT and discrete ripplet transformation are used. Input images are fused at the basic level. Now, three images i.e. two inputs and the fused image are considered input images for the proposed method. These inputs are divided into equal scale blocks. The higher similarity value block is selected for the final fused image.

George *et al.* [18] proposed recognition of palmprint using a combination of ant colony optimization, Gabor filter, and SVM. Ant colony optimization is used for edge detection and the Gabor filter is used for feature extraction. The classification of features is done by an SVM classifier. Pandey*et al.* [19] proposed the score level fusion using ant colony optimization in which score level is available from the features of the inputs. The decision level and score level is given to ACO to take the final decision for fusion. Ant Colony optimization can also be used for image feature selection [20]. Initially, the Gray level co-occurrence matrix is used to collect the properties. These properties are given to ACO to select the optimum features.

Imani*et al.* [21] proposed a feature selector by hybrid ACO and GA. In the feature selection, GA works for search and ACO for the positive feedback. Solanki*et al.* [22] proposed image fusion with a genetic algorithm and curvelet transform. This is obtained by linear superposition, non-linear method, optimization approach, and genetic neural network methods. Somnathe*et al.* [23] proposed a technique for image retrieval using a genetic algorithm. The color and texture properties are collected from the HSV model and co-occurrence matrix respectively. The similarity score of these features is calculated. The weights for these scores are assigned by a genetic algorithm before fusion. Shabu SL *et al.* [24] explained the evolutionary algorithm for multimodal image fusion where curvelet transform and genetic algorithm are used. Inputs are divided for subsets using curvelet transform. Then optimum subband is selected using a genetic algorithm. Arif*et al.* [28] and Gattim*et al.* [30] also explained the multimodal medical image fusion using curvelet transform and genetic algorithm. The use of ACO for image enhancement is explained in [25, 26]. Erkanli*et al.*[27] proposed continuous genetic algorithm by entropy-based image fusion. Han *et al.* [29] proposed the novel technique to fuse visible and infrared images using the two-scale image fusion method. The input images are represented by low rank and saliency parts. The fused image is also obtained in these two parts. The low-rank part is obtained by the adaptive weighted method through particle swarm optimization algorithm.

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The saliency part is obtained by using the average gradient method. Garzelli*et al.* [31] proposed a new technique to merge the multispectral and panchromatic images based on Generalized IHS transformation and genetic algorithm. The GIHS is applied to the multispectral band. The result generated combined with an extracted component from the panchromatic image and the genetic algorithm to find the optimal parameters.

Gao et al.[32] the proposed novel technique about band selection using ACO. Two objective functions based on supervised JM distance and unsupervised simplex volume is introduced. The JM distance measures the distance between the two classes and simplex volume is used for endmember extraction. To improve the quality of extracted endmember, the spatial-spectral preprocessing is done by fusing the spatial and spectral information. Sandip*et al.* [33] suggested a technique to enhance the performance of the multi-biometric system. This is obtained by using score level fusion using ant colony optimization. The features are extracted from two modalities i. e. face and iris and stored in the database. During identification, ACO is used to select the optimum weight to identify the face.

Luan *et al.* [34] proposed a novel hybrid GA and ACO algorithm. This is used to overcome the supplier selection problem. The GA is used to find the optimum solutions. These solutions are used to initiate the ACO pheromone and hence to find the best solution. Yin *et al.* [35] explained the retrieval of urban road information from a very high-resolution image using a direction-guided ACO method. The edge detection and segmentation are done on the input image. Then the edge detected and segmented images are fused. This fused image is given to ACO to initialize the pheromone. Then the best solution is given by ACO.

Huang *et al.* [36] introduced a hybrid genetic algorithm. This is implemented for mutual information-based feature selection wrapper. The trained SVM classifier is used as a fitness function of GA. Khateri *et al.* [37] proposed the spatial-spectral consistency term IF of multispectral and panchromatic images. Structural fidelity is used for panchromatic image and spectral fidelity is used for the multispectral image to preserve the structural and spectral information respectively. Jeong *et al.* [38] explained the multi-guided filter to fuse the infrared and visible images. The multi-guided filter is the modification in the guided filter. This is the real-time IF method.

In this paper, two GA based IF techniques are proposed: a simple integer method and a block method. The results generated by these two methods are presented along with performance parameters. The results of the proposed approach are compared to current approaches and the findings are strengthened. Section II and III explains the proposed Simple Integer Method and Block Method respectively. The result and discussion are given in section IV and section V gives the conclusions.

II. SIMPLE INTEGER METHOD

The name of a simple integer method indicates the type of chromosome used in the IF process. The following steps are used to produce a fused image.

1. Two input images are selected from the mentioned dataset to perform IF. As mentioned in the previous chapter, four types of input images are taken namely multiple sensor RGB which has panchromatic and multispectral images, multi-focus RGB, multiple sensor medical images, and multiple sensor night vision images.
2. GA parameters are set as follows.

Table 1 GA Parameter

GA parameter	Variable	Value
Number of bits in Variable	nBits	8/16 bits
Maximum Iterations	MaxIter	100
Population	Popsize	50
Crossover Percentage	Pc	0.5
Mutation Percentage	Pm	0.3

3. Initially, randomly generating the population matrix with parameters such as popSize. This is the number of chromosomes. For two inputs, separate populations are created. The chromosome value is taken as the weight for an input.

Chromosome structure

An array is created of random numbers of chromosome size where the first index value is 1 and the last value is 255. Put this random array value as the initial population in the genetic algorithm. Then the fitness value i. e. the cost of each chromosome is calculated. Following two figures i.e. Fig. 1*(i)* and 1 *(ii)* illustrate the image fusion process by using only one chromosome set for input images and separate chromosomes for input images respectively.

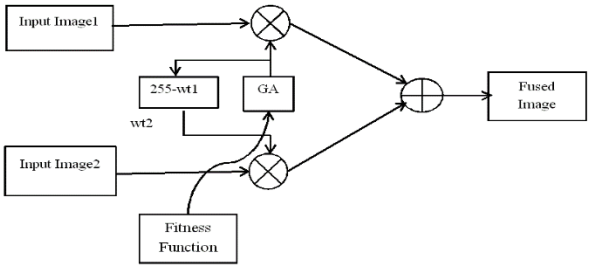

Figure 1 *(i)*: Block diagram of image fusion by a simple integer one population (SIOP) method.

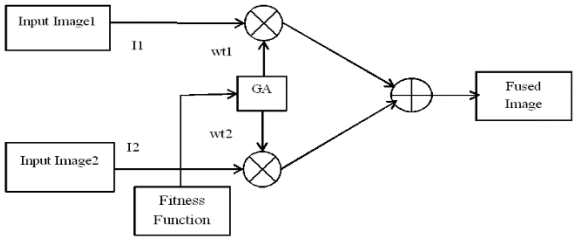

Figure 1 *(ii)*: Block diagram of image fusion by a simple integer separate population (SISP) method.

4) In Fig 1, I1 and I2 are the input images. The weights generated by GA are values of populations. Let wt1 and wt2 be the values of the chromosome of each population. Now, I1 is multiplied by wt1, and I2 is multiplied by wt2. Two new images are available. These images are fused at a simple pixel level using the following formula.

$$F = \frac{wt1*I1+wt2*I2}{wt1+wt2} \quad (1)$$

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The fitness of these individuals in the population is calculated by using a cost function. One of the important quality metrics i.e. root means squared error (RMSE) is used as a fitness function. The RMSE of the resultant image without a reference image is calculated as follows.

$$R1 = \sqrt{\frac{1}{M*N}\sum_{i=1}^{M}\sum_{j=1}^{N}(F(i,j) - I1(i,j))^2} \quad (2)$$

$$R2 = \sqrt{\frac{1}{M*N}\sum_{i=1}^{M}\sum_{j=1}^{N}(F(i,j) - I2(i,j))^2} \quad (3)$$

Here R1 is the cost of an individual in Pop1 value and R2 is the cost of an individual in Pop2 value. These costs are arranged in descending order. The cost is nothing but the RMSE value corresponding to the input image and fused image. The small cost is the best and the large value is the worst. To find the best and worst values from the cost array, sorting is done. Thus, the best and worst value from the cost of each population is taken.

5) Selection of anindividual is based on their fitness value. The individual having more fitness value compare to others has more chance of going to the next generation. Selection probability is calculated by using this equation

$$P = Costs/sum(Costs) \quad (4)$$

Where *Costs* is the value of each individual in the population calculated by using a cost function. As two populations are used, two probabilities are calculated. For population1, probability *P1* is given as

$$P1 = Costs1/sum(Costs1) \quad (5)$$

And for population2, probability *P2* is given as

$$P2 = Costs2/sum(Costs2) \quad (6)$$

Where *Costs1* is the value of each individual in the population1 and *Costs2* is the value of each individual in the population2 calculated by using equations 2 and 3 respectively.

The number of offsprings is taken as *nc*. The parents of these offsprings are selected by using either Roulette Wheel Selection or Tournament Selection criteria.

6) In the Roulette Wheel selection method, cumulative probabilities c[1]…c[popSize] are calculated for each individual in each population. Random numbers r[1]…r[popsize] are generated. The random number is compared with the cumulative probability of each individual. If random number r[1] is greater than c[1] and smaller than c[2] then Chromosome[2] is selected as a Newchromosome[1] in the new population. Likewise, two Newchromosomes are formed from population1and population2.

7) These two parents are used for crossover. The crossover point is generated randomly. If a single-point crossover is used, then one point is generated. And if double point crossover is used, then two points are generated. Let's consider the two parents.

The value of chromosome[6] from population1 is 110 and the value of chromosome[3] from population2 is 168. The binary representations of these two chromosomes are given in Fig 2. Assuming a single crossover is used and the randomly generated crossover point is 5. Now New chromosomes are 174 and 104.

Chromosome 1:

0	1	1	0	1	1	1	0

Chromosome 2:

1	0	1	0	1	0	0	0

New chromosome 1:

0	1	1	0	1	0	0	0

New Chromosome 2:

1	0	1	0	1	1	1	0

Figure 2: Single point crossover representation.

Assuming two-point crossover is used and randomly generated crossover points as 2 and 5. The two-point crossover representation is given in Fig 3.

Chromosome 1:

0	1	1	0	1	1	1	0

Chromosome 2:

1	0	1	0	1	0	0	0

New chromosome 1:

0	1	1	0	1	0	1	0

New Chromosome 2:

1	0	1	0	1	1	0	0

Figure 3: Two-point crossover representation.

Now the new chromosomes are 106 and 172. Likewise, new chromosomes are formed and the cost of each is calculated. Similarly, the mutation is performed in which one or more randomly selected bits are flipped with a small probability to modify the offspring chromosomes. And the above steps are repeated for predefined generations or a specific condition.

III. BLOCK METHOD

In the block method, separate populations are generated like the simple integer technique. Only the distinction lies in the fact that in the block method an array of numbers in one chromosome is generated. The image is divided into blocks. Suppose, image 1 and image 2 are divided into four blocks. Then an array of four numbers is generated randomly. This is one individual in the population. The first block of an image is multiplied by the first number in the array and so on. This is repeated for the second image also. Thus four new blocks of each image are available. Block 1 of image 1 is compared with block 1 of image 2 based on the spatial frequency parameter. The block with a higher spatial frequency is selected. Thus by repeating for remaining blocks of images, the final fused image is available. Then the cost of each chromosome is calculated. The remaining steps are similar to the simple integer method. The block method is represented as follows.

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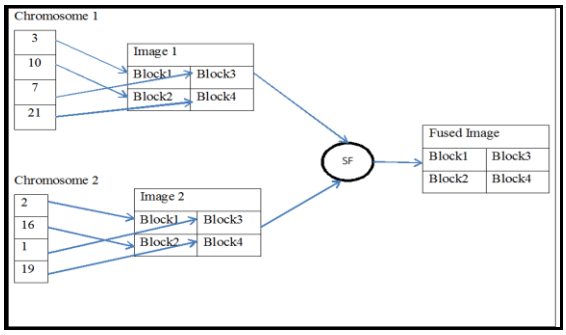

Figure 4: Block method (BM)

IV. RESULTS AND DISCUSSIONS

The image fusion is performed for different input image sets. Here multisensor RGB and multifocus RGB test set of input image are used for SIOP, SISP, and BM methods and compared for visual inspection as well as quality metrics.

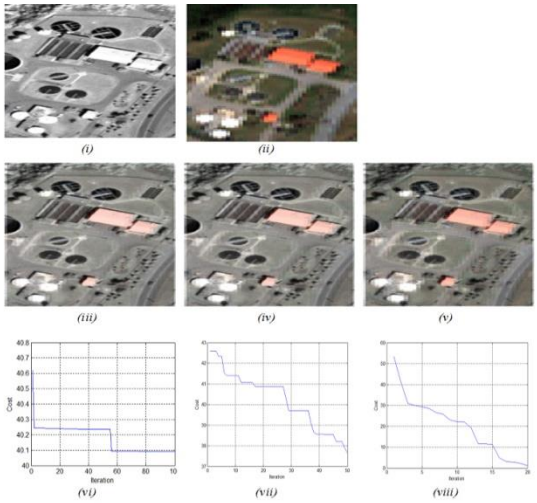

Figure 5: Image fusion of multiple sensor images. *(i)* Image 1, *(ii)* Image 2, *(iii)* to *(v)* are output images obtained by proposed genetic algorithm methods as *(iii)* SIOP, *(iv)* SISP, *(v)* BM, and *(vi)* to *(viii)* are fitness function graph of *(vi)* SIOP, *(vii)* SISP, *(viii)* BM methods

Figures 5 show the results generated for multiple sensor RGB inputs. At first glance, no major differences between these images can be found. However, after a thorough analysis of the displayed output images, Fig. 5*(v)* is clearer and smooth. From the fitness behavior graph, the fitness of SIOP remains stable for some iterations and then changing whereas, in SISP and BM, the fitness is continuously changing towards the optimized result. Table 2 show the performance parameters of image fusion by SIOP, SISP, and BM techniques for multiple sensor RGB inputs respectively.

Table 2 Performance parameters of image fusion by SIOP, SISP, BM techniques for multiple sensor images.

Quality Metrics	SIOP	SISP	BM
Mean	132.99	114.99	113.46
Entropy	7.21	7.26	7.92
Var	1772.15	1723.24	5033.45
StdDev	42.1	41.51	70.95
RMSE	38.95	31.46	0.71
PSNR	31.24	37.79	31.04
SF	20.92	18.79	45.97
MI	2.54	2.45	3.58
IQI	0.18	1	1
AG	8.58	7.39	2.66

From table 2, the BM technique is giving better performance than SIOP and SISP. Fig. 6 shows the results generated by the image fusion for multifocus RGB images. The output obtained by SIOP is highly insightful than SISP and BM. Table 3 gives the performance parameters of image fusion by SIOP, SISP, and BM techniques for multifocus images. In this, RMSE, SF, and AG are good whereas MI is superior in SIOP.

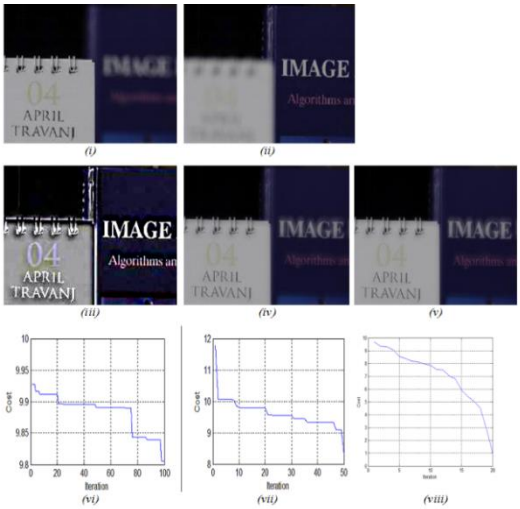

Figure 6: Image Fusion for multifocus RGB images. *(i)* Image 1, *(ii)* Image 2, *(iii)* to *(v)* are output images obtained by proposed genetic algorithm methods as *(iii)* SIOP, *(iv)* SISP, *(v)* BM, and *(vi)* to *(viii)* are fitness function graph of *(vi)* SIOP, *(vii)* SISP, *(viii)* BM methods.

V. CONCLUSIONS

The genetic algorithm is giving optimized output. Three different methods are used in the implementation as GA with one population, the GA with separate populations, and the block method. The output images obtained using these proposed methods are compared visually. For multiple sensor satellite input images, BM is observed to be superior to SIOP and SISP. For multifocus input images, simple method one population is giving better output than the rest of the methods but with some artifacts. By observing the representation of performance parameters, the block method is giving better performance for RMSE and PSNR whereas SISP is superior for the remaining parameters

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