A Novel Approach to Image Fusion Based on Multi-Objective Optimization

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Abstract - Most approaches to image fusion determine the building of image fusion model based on experience, and the parameter configuration of the fusion model is somewhat arbitrary. In this paper, a novel approach to image fusion based on multi-objective optimization was presented, which could achieve the optimal fusion indices through optimizing the fusion parameters. First the uniform model of image fusion in DWT (Discrete Wavelet Transform) domain was established; then the proper evaluation indices of image fusion were given; and finally the adaptive multi-objective particle swarm optimization (AMOPSO) was introduced to search the optimal fusion parameters. Experiment results show that AMOPSO has a higher convergence speed and better exploratory capabilities than MOPSO, and that the approach to image fusion based on AMOPSO realizes the Pareto optimal image fusion.

Index Terms - multi-objective image fusion; adaptive multi-objective particle swarm optimization (AMOPSO)

I. INTRODUCTION

Image fusion is a valuable process in combining images with various spatial, spectral and temporal resolutions to form new images with more information than that can be derived from each of the source images [1]. Different methods of image fusion have the same objective, that is, to acquire a better fusion effect. Different methods have the given parameters, and different parameters could result in different fusion effects. In general, we establish the parameters based on experience or the parameters adaptively change with the image contents, so it is fairly difficult to gain the optimal fusion effect. If one image is regarded as one information dimension or a feature subspace, image fusion can be regarded as an optimization problem in several information dimensions or the feature space. A better result, even the optimal result, can be acquired through searching the optimal parameters and discarding the given values in the process of image fusion. Therefore, a proper search strategy is very important for the optimization problem. In [2], the optimization of image fusion was primarily explored, and the objective is the mean square error (MSE), but only one objective is too simple to meet the real demands.

In fact, there are various kinds of evaluation indices, and different indices may be compatible or incompatible with one another, so a good evaluation index system of image fusion must balance the advantages of different indices. The traditional solution is to change the multi-objective problem into a single objective problem using weighted linear method. However, the relation of the indices is often nonlinear, and this method needs to know the weights of different indices in advance. So it is highly necessary to introduce multi-objective optimization methods based on Pareto theory to search the optimal parameters in order to realize the optimal image fusion, by which the solutions are more adaptive and competitive because they are not limited by the given weights.

At present, multi-objective optimization algorithms include Pareto Archive Evolutionary Strategy (PASE) [3], Strength Pareto Evolutionary Algorithm (SPEA2) [4], Nondominated Sorting Genetic Algorithm II (NSGA-II) [5], Nondominated Sorting Particle Swarm Optimization (NSPSO) [6], Multiple Objective Particle Swarm Optimization (MOPSO) [7], [8], etc. Lots of experiments with the two objective optimization problems show that MOPSO has a better optimization capacity and a higher convergence speed [7]. However, MOPSO uses an adaptive grid [3] to record the searched particles, which need too much calculation time, and may cause failure in allocating memory, even in integer format. Using MOPSO and NSGA-II for reference, we present an adaptive multi-objective particle swarm optimization (AMOPSO) to optimize the fusion model. In contrast to other multi-objective evolutionary algorithms, AMOPSO has a higher convergence speed and better exploratory capabilities.

The approach to image fusion based on AMOPSO is more successful. Different from the conventional approaches, the image fusion model is simplified in the approach, and the emphasis is laid on the multi-objective optimization. Through optimizing multiple objectives, the optimal image fusion can be achieved.

II. IMAGE FUSION IN DWT DOMAIN

As shown in Fig. 1, the approach to image fusion based on multi-objective optimization in DWT domain is as follows.

Step 1: Input the registered source images $A$ and $B$. Find the DWT of each $A$ and $B$ to a specified number of decomposition levels, at each level we will have one-approximation sub band and $3\times J$ details, where $J$ is the decomposition level. If the value of $J$ is too high, the pixels in sub images will cause the distortion, otherwise the decomposition can’t embody the advantage of multiple scales. In general, $J$ is not greater than 5. When $J$ equals 0, the transform result is the original image and the fusion is performed in spatial domain.
A rule called "uniform weight method (UWM)" is given by

\[ w_i = \frac{1}{\sum_j w_j}, \quad i = 1, \ldots, J \]

where \( w_i \) is the weighted factor of the \( i \)-th coefficient. The selection mode is implemented as follows:

\[ W_{\text{fused}}(x, y) = \begin{cases} W_{\text{current}}(x, y), & S_{\text{current}}(x, y) \geq S_{\text{fused}}(x, y) \\ W_{\text{current}}(x, y), & \text{otherwise} \end{cases} \]

where \( W_{\text{fused}}(x, y) \) are the final fused coefficients in DWT domain, \( W_{\text{current}}(x, y) \) and \( S_{\text{current}}(x, y) \) are the current coefficients and salience of images \( A \) and \( B \) at level \( j \).

The coefficient with the largest salience is substituted for the fused coefficient while the less salient coefficient is discarded. The selection mode is implemented as follows:

\[ W_{\text{fused}}(x, y) = \begin{cases} W_{\text{current}}(x, y), & S_{\text{current}}(x, y) \geq S_{\text{fused}}(x, y) \\ W_{\text{current}}(x, y), & \text{otherwise} \end{cases} \]

where \( W_{\text{current}}(x, y) \) are the final fused coefficients in DWT domain, \( W_{\text{current}}(x, y) \) and \( S_{\text{current}}(x, y) \) are the current coefficients and salience of images \( A \) and \( B \) at level \( j \).

Step 3: For approximations in DWT domain, use weighted factors to calculate the approximation of the fused image. Let \( C_A, C_B \) be the approximations of \( A, B \) respectively. Using multi-objective optimization methods, we can find the optimal decision variables of image fusion in DWT domain, and realize the optimal image fusion.

Step 4: The new sets of coefficients are used to find the inverse transform to get the fused image \( F \).

### III. EVALUATION INDICES OF IMAGE FUSION

In our approach to image fusion, the establishment of an evaluation index system is the basis of the optimization that determines the performance of the final fused image. However, in the image fusion literature only a few indices for quantitative evaluation of different image fusion methods have been proposed. Generally, the construction of the perfect fused image is an ill-defined problem since in most case the optimal combination is unknown in advance. In this study, we explore the possibility to establish an impersonal evaluation index system and get some meaningful results.

In fact, the evaluation indices of image fusion include subjective indices and objective indices. Subjective indices rely on the ability of people's comprehension and are hard to come into application. While objective indices can overcome the influence of human vision, mentality and knowledge, and make machines automatically select a superior algorithm to accomplish the mission of image fusion.

Objective indices can be divided into three categories based on subjects reflected. One category reflects the image features, such as entropy and gradient. The second reflects the relation of the fused image to the source images, such as mutual information. And the third reflects the relation of the fused image to the standard image, such as correlation coefficient, peak signal to noise ratio (PSNR).

#### A. Image feature Indices

Image feature indices are used to evaluate the quality of the fused image.

1) **Entropy**: Entropy is an index to evaluate the information quantity contained in an image. If the value of entropy becomes higher after fusing, it indicates that the information quantity increases and the fusion performance is improved. Entropy is defined as

\[ E = -\sum_{i=0}^{L-1} p_i \log_2 p_i \]

where \( L \) is the total of grey levels, \( p_{\{0,1,\ldots,L-1\}} \) is the probability distribution of each level.

2) **Gradient**: Definition reflects the change rate in image details that can be used to represent the clarity degree of an image. The higher the gradient of the fused image is, the clearer it is. Gradient is given by

\[ \bar{g} = \frac{\sum_i \sqrt{[F(x, y) - F(x+1, y)]^2 + [F(x, y) - F(x, y+1)]^2}}{\sqrt{2(M-1)(N-1)}} \]

where \( M \) and \( N \) are the numbers of the row and column of the image respectively.

#### B. Mutual Information Indices

Mutual information indices are used to evaluate the correlative performances of the fused image and the source images. Let \( A \) and \( B \) be two random variables with marginal
probability distributions \( p_A(a) \) and \( p_B(b) \), and joint probability distribution \( p_{AB}(a, b) \), mutual information is defined as [10]

\[
I_{AB} = \sum p_{AB}(a, b) \cdot \log \left[ \frac{p_{AB}(a, b)}{(p_A(a)p_B(b))} \right] 
\]  

(7)

1) Mutual Information: A higher value of mutual information (MI) indicates that the fused image contains fairly good quantity of information presented in both the source images. MI is given by

\[
MI = I_{AF} + I_{BF} 
\]  

(8)

2) Information Symmetry: A high value of MI doesn’t imply that the information from both the images is symmetrically fused. Therefore, information symmetry (IS) is introduced [11]. IS is an indication of how much symmetric the fused image is, with respect to input images. The higher the value of IS, the better the fusion result is. IS is given by

\[
IS = 2 - \text{abs}[I_{AF} / (I_{AF} + I_{BF}) - 0.5] 
\]  

(9)

C. Structural Similarity Indices

The structural similarity indices can evaluate the relation of the fused image to the standard image.

1) Structural Similarity: Structural similarity (SSIM) is designed by modeling any image distortion as a combination of three factors: loss of correlation, radiometric distortion, and contrast distortion [12], [13]. SSIM is defined as

\[
SSIM = \frac{\sigma_{FR}}{\sigma_{F} \sigma_{R}} \cdot \frac{2\mu_{F}\mu_{R}}{\mu_{F}^{2} + \mu_{R}^{2}} \cdot \frac{2\sigma_{F}\sigma_{R}}{\sigma_{F}^{2} + \sigma_{R}^{2}} 
\]  

(10)

where \( \mu_{F}, \mu_{R} \) is the mean intensity of the fused image \( F \) and the standard image \( R \) respectively, \( \sigma_{F}, \sigma_{R}, \sigma_{FR} \) is the standard deviation (the square root of variance) of \( F \) and \( R \).

In (10), the first component is the correlation coefficient for \( F \) and \( R \). The second component measures how close the mean grey levels of \( F \) and \( R \) is, while the third measures the similarity between the contrasts of \( F \) and \( R \). The dynamic range is [-1, 1]. The higher the value of SSIM is, the more similar to \( R \) the \( F \) is. If two images are identical, the similarity is maximal and equals 1.

2) Peak Signal to Noise Ratio: The higher the value of PSNR is, and the lower the value of RMSE is, the better the fused image is. PSNR is defined as

\[
PSNR = 10 \log_{10} \frac{255^{2}}{\text{RMSE}^{2}} 
\]  

(11)

where RMSE (root mean squared error) is defined as

\[
\text{RMSE}^{2} = \frac{1}{MN} \sum_{i,j} \left[ R(i,j) - F(i,j) \right]^{2} 
\]  

(12)

IV. AMOPSO ALGORITHM

J. Kennedy and R. C. Eberhart brought forward particle swarm optimization (PSO) inspired by the choreography of a bird flock in 1995 [14]. Unlike conventional evolutionary algorithms, PSO possesses the following characteristics: 1) Each individual (or particle) is given a random speed and flows in the decision space; 2) each individual has its own memory; 3) the evolution of each individual is composed of the cooperation and competition among these particles.

Since the PSO was proposed, it has been of great concern and become a new research field. PSO has shown a high convergence speed in single objective optimization [15], and it is also particularly suitable for multi-objective optimization [7], [8], [16]. In order to improve the performances of the algorithm, we present a proposal, called “adaptive multi-objective particle swarm optimization” (AMOPSO) [17], in which not only an adaptive mutation operator is used to avoid earlier convergence, but also a crowding distance operator is used to improve the distribution of nondominated solutions along the Pareto front and maintain the population diversity [5], and an adaptive concave exponent inertia weight is used to raise the searching capacity. The flow of AMOPSO is as follows.

A. Algorithm Initialization

Initialize the population and algorithm parameters.

1) Initialize the position of each particle: \( \text{pop}[i] \), where \( i=1, ..., NP \) is the particle number.

2) Initialize the speed of each particle: \( \text{vel}[i]=0 \)

3) Initialize the record of each particle: \( \text{pbests}[i]=\text{pop}[i] \)

4) Evaluate each of the particles in the \( \text{POP} \): \( \text{fun}[i, j] \), where \( j=1, ..., NF \), and \( NF \) is the objective number.

5) Store the positions that represent nondominated particles in the repository of the \( \text{REP} \) according to the Pareto optimality.

B. Program Execution

Before the maximum number of cycles is reached, do

1) Update the speed of each particle using (13).

\[
\text{vel}[i] = W \cdot \text{vel}[i] + c_{1} \cdot \text{rand}_{1} \cdot (\text{pbests}[i] - \text{pop}[i]) + c_{2} \cdot \text{rand}_{2} \cdot (\text{rep}[h] - \text{pop}[i]) 
\]  

(13)

where \( W \) is the inertia weight [18]; \( c_{1} \) and \( c_{2} \) are the learning factors [19], \( \text{rand}_{1} \) and \( \text{rand}_{2} \) are random values in the range \([0, 1]\), \( \text{pbests}[i] \) is the best position that the particle \( i \) has had; \( h \) is the index of the maximum crowding distance in the repository that implies the particle locates in the sparse region, as aims to maintain the population diversity; \( \text{pop}[i] \) is the current position of the particle \( i \).

2) Update the new positions of the particles adding the speed produced from the previous step

\[
\text{pop}[i] = \text{pop}[i] + \text{vel}[i] 
\]  

(14)
3) Maintain the particles within the search space in case they go beyond their boundaries. When a decision variable goes beyond its boundaries, the decision variable takes the value of its corresponding boundary, and its velocity is multiplied by (-1).
4) Adaptively mutate each of the particles in the POP at a probability of $P_m$.
5) Evaluate each of the particles in the POP.
6) Update the contents in the REP, and insert all the current nondominated positions into the repository.
7) Update the records, when the current position of the particle is better than the position contained in its memory, the particle’s position is updated.

$$p_{best}(i) = pop(i)$$

(15)

8) Increase the loop counter of $g$.

V. RESULTS

The performance of the proposed image fusion approach was tested and compared with that of different fusion schemes. The image “plane” was selected as the standard image $R$. Through image processing, we got two source images $A$ and $B$. As shown in Fig. 2(a) and (b), the left region of $A$ is blurred, while the right region of $B$ is blurred. We used AMOPSO to search the Pareto optimal weights of the fusion model and compared the results with those of MOPSO based method and simple wavelet method (SWM) [11].

The parameters of AMOPSO are as follows: the particle number of $NP$ is 100; the objective number of $NF$ is 6; the inertia weight of $W_{max}$ is 1.2, and $W_{min}$ is 0.2; the learning factor of $c_1$ is 1, and $c_2$ is 1; the maximum cycle number of $G_{max}$ is 100; the allowed maximum capacity of $MEM$ is 100; the mutation probability of $P_m$ is 0.05. The parameters of MOPSO are the same, while the inertia weight of $W$ is 0.4, the grid number of $N_d$ is 20, for a greater number may cause the failure of program execution, e.g. 30. The sum of the weights at each position of two source images is limited to 1. All approaches are run for a maximum of 100 evaluations.

Since the solutions to the optimization of image fusion are nondominated by one another, we give preference to the six indices so as to select the Pareto optimal solutions to compare, e.g. one order of preference is SSIM, MI, Entropy, PSNR, Gradient, IS. When the standard image doesn’t exist, the MI will become the principal objective.

The fused images from the Pareto optimal solutions are shown in Fig. 2(c), (d), (e), and (f). It is possible that the fused image of AWM at decomposition level 5 is the best. Table I shows the evaluation indices of the fused images from different schemes, where AWM I is the AWM with a linear inertia weight (see [18]), AWM II is the AWM without the mutation operator, AWM III is the AWM with the crowding distance of NSGA-II (see [5]), MOPSO denotes the AWM based on MOPSO (see [7]), SWM uses the schemes in [11].

From Table I, we can see that when the decomposition level equals zero in DWT domain, which is in spatial domain, the indices of AWM (Fig. 2(d)) are inferior to those of UWM (Fig. 2(c)). The reason is that the decision variables of AWM in spatial domain are too many and AWM can’t reach the Pareto optimal front in a limited time, e.g. the number of iteration is 100. The run time of AWM must increase with the number of decision variables, so AWM can only be regarded as an ideal method of image fusion in spatial domain. The advantage of spatial fusion is easy to realize, however the simple splice of pixels smooths the image and is not convenient for the later processing, such as comprehension.

In DWT domain, the indices of AWM at level 5 (Fig. 2(f)) are superior to those of UWM at other levels. The higher the decomposition level is, the better the fused image is, for a higher level decreases the decision variables and improves the adaptability. Moreover, the indices of AWM are superior to those of UWM because the weights of AWM are adaptive in different regions.

The indices of SWM are inferior to our results except IS and time. In fact, IS can’t be used as an important objective, e.g. IS reaches the maximum in A and B before fusing. The less time of SWM is due to the simplicity of algorithm. The indices of AWM I, II, III and MOPSO are inferior to those of AWM at level 5, which indicates the adaptive concave exponent weight is superior to the linear weight; the mutation operator can avoid earlier convergence; the new crowding distance can increase the running speed and achieve better results, MOPSO needs too much memory because the grid [3] is worse for too many objectives, e.g. 6.

Therefore, the approach to image fusion that uses AMOPSO to search the adaptive fusion weights at level 5 in DWT domain is the optimal. This approach can save up the optic features of the images in contrast to the spatial approach, overcome the limitations of given parameters, and obtain the optimal fusion performances.
VI. CONCLUSIONS

The approach using AMOPSO to optimize the model parameters of image fusion is feasible and relatively effective, and can get the Pareto optimal fusion result. Multi-objective optimization for the fusion parameters can avoid the limitations of too heavy dependence on the experience and simplify the algorithm design for image fusion. Once the valid evaluation indices are established, the method of multi-objective optimization can be used to deal with these objectives that could conflict with one another and eliminate the influence of preference effectively. The proposed AMOPSO is an effective algorithm to solve the multi-objective problem, which can get to the Pareto front of optimization problems quickly and attain the optimal solutions.

One aspect that we would like to explore in the future is the analysis for the evaluation indices system using PCA to simplify the algorithm design for image fusion. Once the valid evaluation indices are established, the method of multi-objective optimization can get to the Pareto optimal fusion result. Multi-objective optimization for the fusion parameters can avoid the influence of preference effectively. The proposed AMOPSO is an effective algorithm to solve the multi-objective problem, which can get to the Pareto front of optimization problems quickly and attain the optimal solutions.

REFERENCES


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### TABLE I

**EVALUATION INDICES OF THE FUSED IMAGES FROM DIFFERENT SCHEMES**

<table>
<thead>
<tr>
<th>Schemes</th>
<th>Level</th>
<th>Entropy</th>
<th>Gradient</th>
<th>MI</th>
<th>IS</th>
<th>PSNR</th>
<th>SSIM</th>
<th>Time (s)</th>
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<tbody>
<tr>
<td>Image A</td>
<td>0</td>
<td>6.4272</td>
<td>6.7631</td>
<td>29.7198</td>
<td>1.9998</td>
<td>25.8193</td>
<td>0.955731</td>
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<td>6.9881</td>
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<td>1.9996</td>
<td>26.5760</td>
<td>0.963261</td>
<td>-</td>
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<tr>
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<td>6.3220</td>
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<td>0.979466</td>
<td>199.72</td>
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9915