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Fusion of Visible and Infrared Images using Multiobjective Evolutionary Algorithm Based on Decomposition

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Abstract: Integration of images from different sensing modalities can produce information that cannot be obtained by viewing the sensor outputs separately and consecutively. In order to enhance the contrast of the fused image and reduce the loss of fine details in the process of image fusion, an innovative fusion method of visible and infrared images is presented in this paper, which uses a multiobjective evolutionary algorithm based decomposition (MOEA/D). First of all, we employ contrast pyramid (CP) decomposition into every level of each original image. Second, MOEA/D is introduced to optimize fusion coefficients, thus the weighted coefficients can be adjusted automatically according to fitness function. Finally, obtain the fused images by the weight integration of the optimal fusion coefficients and CP reconstruction. Experimental results show that the fusion algorithm proposed in this paper achieves better effect than the other fusion algorithms both in visual effect and quantitative metrics, and the fused images are more suitable for human visual or machine perception.

Keywords: Image fusion, visible and infrared images, MOEA/D, multiobjective optimization

1. Introduction

Image fusion is the process of integrating multiple registered images of the same scene into a single fused image to reduce uncertainty and minimizing redundancy while extracting all the useful information from the source images [1, 2]. The goal of the image fusion is to generate the composite image, which is more informative than its input images. The existing image fusion approaches can be classified into three categories: pixel-level, feature-level, and decision-level [3]. This paper is focused on the pixel-level fusion approach. A large number of image fusion methods [4-7] have been proposed in literature.

In addition to the above taxonomy, the strategies of image fusion can be classified into two types: simple fusion strategy and layered fusion strategy. While the former has several simple fusion rules that utilize localized spatial features such as logarithmic filtering, gray-weighting average, contrast adjustment and so on [8-11], the latter includes the fusion strategy based on decomposition , for instance, pyramid, wavelet and curvelet transform fusions [12-15]. However, the drawback of the wavelet transform is that it cannot perform well when the edges are smooth curves because of their limited ability in capturing directional information. Although contourlets in two dimensions can solve this problem, which have the property of capturing contours and fine details in images [16], there are still two drawbacks: (1) do not consider information from higher levels of abstraction, (2) lose some detailed texture information and important spectral information.

To overcome the drawbacks mentioned above, a novel approach for the fusion of visible and infrared images is proposed in this paper, using multiobjective evolutionary algorithm based on decomposition (MOEA/D) [17]. It decomposes a multiobjective optimization problem into a number of scalar optimization subproblems and optimizes them simultaneously. Each subproblem is optimized by only using information from its several neighboring subproblems, which makes MOEA/D have lower computational complexity at each generation. Besides, MOEA/D using objective normalization can deal with disparately-scaled objectives, and MOEA/D with an advanced decomposition method can generate a set of very evenly distributed solutions for 3-objective test instances.

The remainder of the paper is organized as follows. In Section 2, we briefly review that what is multiobiective optimization problem, and introduce the MOEA/D principle in detail. Section 3 describes how to combine contrast pyramid decomposition with MOEA/D for fusion of visible and infrared images. The experimental results and performance analysis are concretely given in Section 4. The conclusions are drawn in Section 5.

2. MOEA/D algorithm

2.1 Multiobjective optimization problem

Multiobjective optimization problem (MOP), is that the optimization goals of optimization problem are more than one and need to be processed at the same time [18-23], and every subgoal is contradictory from each other, so it is impossible to make each subgoal to achieve the optimal value simultaneously. There are often a group of noninferior solutions, which is also called Pareto optimal solution. From [21], MOP has its mathematical form, which can be described as follows:

$$\begin{gathered} \text{maximize } F(X) = \left(f_1(X), f_2(X) ..., f_k(X)\right) \\ k = 1, 2, ..., N \\ X = \left[x_1, x_2, ...x_d, ..., x_D\right] \\ x_{d\_\min} \le x_d \le x_{d\_\max} \qquad d = 1, 2, ...D \end{gathered} \tag{1}$$

Where, X is a D-dimension decision vector, $x_{d\_\min}$, $x_{d\_\max}$ denote the search upper and lower of each dimension vector, respectively. In addition, $F(X)$ is objective vector and k is the total number of the optimization goal. It also allows the existing of the constraint functions for X.

The definition of Pareto optimal [24] solution is not dominated by an arbitrary solution in the feasible solutions, if X^* is a point in the search space, says X^* is the optimal solution of inferior quality, only when there is no X make $f_i(X) \ge f_i(X^*)$, $i = 1, 2, ..., k$. The collection of all the optimal solutions of inferior quality is the optimal solution set of MOP, which is called Pareto optimal set or Pareto front.

2.2 MOEA/D algorithm principle

Qingfu Zhang, etc, firstly propose the multiobjective evolutionary algorithm based on decomposition [17], and introduce three approaches that it can be used in the evolutionary algorithm framework proposed in their paper. Considering the performance, we adopt Tchebycheff approach to decompose the multiobjective problem established in the field of image fusion. The scalar optimization problem is as the following form.