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A novel fusion scheme for visible and infrared images based on compressive sensing

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ABSTRACT

An appropriate fusion of infrared and visible images can integrate their complementary information and obtain more reliable and better description of the environmental conditions. Compressed sensing theory, as a low signal sampling and compression method based on the sparsity of signal under a certain transformation, is widely used in various fields. Applying to the image fusion applications, only a part of sparse coefficients are needed to be fused. Furthermore, the fused sparse coefficients can be used to accurately reconstruct the fused image. The CS-based fusion approach can greatly reduce the computational complexity and simultaneously enhance the quality of the fused image. In this paper, an improved image fusion scheme based on compressive sensing is presented. This proposed approach can preserve more detail information, such as edges, lines and contours in comparison to the conventional transform-based image fusion approaches. In the proposed approach, the sparse coefficients of the source images are obtained by discrete wavelet transform. The low and high coefficients of infrared and visible images are fused by an improved entropy weighted fusion rule and a max-abs-based fusion rule, respectively. The fused image is reconstructed by a compressive sampling matched pursuit algorithm after local linear projection using a random Gaussian matrix. Several comparative experiments are conducted. The experimental results show that the proposed image fusion scheme can achieve better image fusion quality than the existing state-of-the-art methods.

1. Introduction

In the last decade, with extraordinary advances in sensor technology, numerous imaging sensors have been applied in military and civilian applications. Infrared (IR) and visible images, as two wildly used image modalities, contain quite different and complementary information [1–8]. IR images can provide a promising alternative to visible images and have a good radiometric resolution, but IR image sensors are sensitive to the difference of temperature in the surrounding environment. Interestingly, visible images can provide more detail information since the visual sensor interprets the surrounding environment by processing information that is contained in visible light. Thus, an appropriate fusion of IR and visible images can combine the complementary information and obtain a more reliable and better description of the environmental conditions. The image fusion approach for IR and visible images can improve spatial awareness, increase accuracy in target detection and recognition, reduce operator workload and increase system reliability [3–8]. The fusing of the two kinds of images has attracted more attention due to its widespread use in many fields such as night vision and video surveillance [4–8].

Many fusion schemes of IR and visible images have been proposed in recent years. These can be classified into: pixel level fusion, feature level fusion and decision level fusion. In comparison to feature and decision-level fusion, pixel-level fusion affords much more original information. Among the presented fusion methods, multi-scale transform-based image fusion methods are popularly used in the pixel-level fusion domain, including discrete wavelet transform (DWT) [5,6], stationary wavelet transform (SWT) [7,8], dual-tree complex wavelet transform (DT-CWT) [9,10], curvelet transform [11], ridgelet transform [12], contourlet transform [13,14], etc. Therefore, Indhumadhi and Padmavathi utilize Laplacian fusion algorithm and SF algorithm to fuse the low and high approximations by applying 2D-DWT in order to

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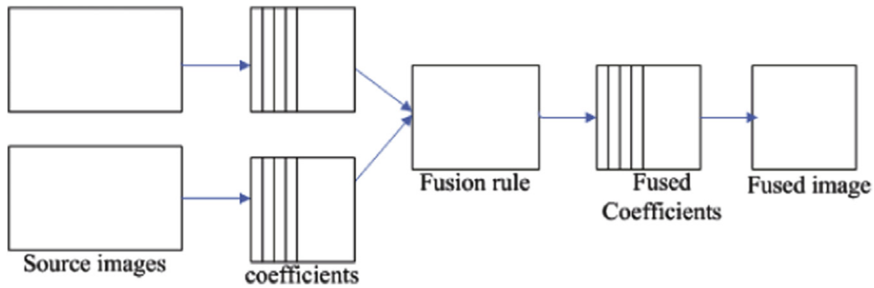

Fig. 1. The conventional transform-based image fusion scheme.

enhance the performance of the fused image [15]. Mirajka and Sachin explore transform fusion based on SWT to acquire more edge image information and this method achieves better quality [16]. Hill et al. introduce a novel image fusion approach based on the shift invariant and DT-CWT [17]. Fig. 1 shows a generic fusion scheme in a transform domain which is widely used [12,14,18,19]. In this scheme, there are two different approaches to select the transform coefficients. One approach merges all of the coefficients of source images to obtain high-quality fused image. The other approach integrates a number of sparse coefficients by applying the constrained threshold to enhance the speed of reconstruction.

However, the two fusion approaches both have disadvantages specific to the different coefficient selection methods. Although the fusion approach can achieve better fused image quality by combining all of the coefficients. It suffers in the high computational complexity. In the real applications, it may lead to the problems of "Information overload". Correspondingly, only merging certain coefficients can greatly reduce the computational complexity, but the quality of the integrated image cannot be guaranteed. The key problem is how to select the constrained threshold. It usually depends on the priori knowledge of source images [4,12,18]. The selection of the ill-suited threshold may result in the problems of blocking artifacts and poor fidelity. In comparison, the compressive sensing (CS) theory can accurately construct high-quality merged image via fusing fewer sparse coefficients. The only constrained condition is the coefficients should be sparse [20–24]. While, in the transform domain almost all the transform coefficients are sparse. In practical applications, the compressive sensing theory can be utilized to overcome the problems of "information overload", blocking artifacts and poor fidelity [20–24]. Due to these merits, various image fusion approaches based on compressive sensing are proposed. Li and Qin give out a novel self-adaptive weighted average fusion scheme based on standard deviation of measurements to merge IR and visible images. It uses the better recovery tool of total variation optimization in the special domain of compressive sensing [21]. Looney and Mandic takes advantage of complex-valued image processing empirical mode decomposition to optimize the quality of the fused image [25]. Chen and Xiao propose a novel multi-sensor image fusion algorithm based on distributed compressive sensing [26]. Yang and Li propose a novel image fusion scheme using the sparse representation theory [27]. However, there are two major limitations above all these algorithms. Initially, only one fusion rule is used to integrate different coefficients. It perhaps leads to blocking artifacts and poor fidelity for multi-source images. Secondly, these methods produce much more reconstruction error because of focusing on fusing the measurements.

In this work, an improved fusion scheme for visible and infrared images based on compressive sensing is proposed. In our proposed fusion approach, firstly, DWT is utilized to acquire the sparse coefficients: approximation coefficients and detail coefficients. Then, an improved entropy weighted fusion rule is used to fuse the low-frequency information; the max-abs-based fusion rule is employed to integrate the high-frequency information. These can remove the blocking artifacts problem and enhance the quality of the fused image. Finally, the fused image can be reconstructed by Compressive Sampling Matched Pursuit algorithm (CoSaMP) after non-adaptive linear projection exploring a random Gaussian matrix. In particular, the CS-based image fusion approach only fuses fewer sparse coefficients and accurately reconstructs the fused image in comparison to the transform-based fusion scheme. It also means that computation complexity is greatly reduced and concurrently the quality of the integrated image is enhanced. The key contributions of this work can be elaborated as follows:

(1) An improved CS-based image fusion scheme for infrared and visible images is proposed. Directly fuse the sparse coefficients before non-adaptive linear projection may reduce the reconstruction error. Furthermore, the proposed fusion approach is not limited to image fusion for the IR and visible images. It also can extend to the other image fusion applications.

(2) An improved fusion rule based on entropy and mutual information is proposed to preserve more detail information, such as edges, lines and contours. In this work, the proposed fusion rule and the maximum selection fusion rule are utilized to fuse the low and high frequency information, respectively. These can generate quite satisfying results with good removal of visual artifacts.

2. The proposed fusion framework

Reviewing image fusion in CS domain, one intuitional way is to fuse the linear projections before reconstructing the integrated image. However, in a real scenario, it is hard to obtain the accurate measurements. To overcome this limitation, directly merging the sparse coefficients is a proper solution. Employing this method, priori information of the source images is not necessary. It simplifies the algorithmic implementation of our proposed fusion method. The framework of the image fusion approach based on compressive sensing is indicated in Fig. 2.

In this approach, multi-layer discrete wavelet transform is utilized to represent the visible and IR images [6,18]. The key merits of DWT are its high compression ratios and good localization. The complementary coefficients illustrate the approximation and detail components of the input images. Correspondingly, the decompositions of coefficients can be denoted by

$$
\begin{aligned}
A_{l-1}(i,j) &= \sum_{m,n\in R} \hat{h}(m)\hat{h}(n)A_l(2i-m,2j-n)\\
D^1_{l-1}(i,j) &= \sum_{m,n\in R} \hat{h}(m)\hat{g}(n)A_l(2i-m,2j-n)\\
D^2_{l-1}(i,j) &= \sum_{m,n\in R} \hat{g}(m)\hat{h}(n)A_l(2i-m,2j-n)\\
D^3_{l-1}(i,j) &= \sum_{m,n\in R} \hat{g}(m)\hat{g}(n)A_l(2i-m,2j-n), \qquad (1)
\end{aligned}
$$