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Noise Resilient Image Fusion Based on Orthogonal Matching Pursuit

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***Abstract*—A novel image fusion algorithm based on orthogonal matching pursuit(OMP) is proposed, which is named IFOMP algorithm and can be used for noise free or noise images. The matching pursuit algorithm provides an efficient image representation using an overcomplete dictionary. Firstly, the source images are decomposed into sub-images at different scales through laplacian pyramid transform. The OMP method is exploited for capturing and fusing edges and texture feaures in the high frequency domain. Experimental results show that the proposed algorithm improves performance compared to traditional wavelet fusion with slightly increased computational complexity, and the fusion image has good robustness.**

***Keywords*—image fusion, orthogonal matching pursuit, laplacian pyramid, overcomplete dictionary**

I. INTRODUCTION

With the development of multi-sensors in many fields such as remote sensing, machine vision, medical imagery and millitary applications, image fusion has emerged as a new and important research area.

Many image fusion techniques and toolboxes have been developed since then. In recent years, wavelet transform has been most commonly used in image fusion and many research achievements have been gotten[1-4]. Wavelets provide a good representation for the natural images containing smooth areas with edges. However, natural images in reality are very complicated, which may present various kinds of geometry structures. For example, it is hopeless to analyze a mixture of curves and textures with wavelet decomposition.

In order to search for powerful representation, Mallat and Zhang[5] originally proposed the theory of signal sparse decomposition with redundant dictionaries and three basis selection algortithms were proposed: matching pursuit(MP), orthogonal matching pursuit(OMP)[6] and basis pursuit(BP). Comparing with other two methods, the OMP algorithm maintains the backward orthogonality of the residual and leads to a better convergence. In this paper, we present a novel image fusion method based on orthogonal matching pursuit, and call it IFOMP algorithm. In the IFOMP, using orthogonal matching pursuit algorithm (OMP), different kinds of local frequency components from source images are iterally extracted and fused together after comparison. Considering the OMP algorithm is redundant and overlapped, blocking or rings artifacts of fused image can be efficiently avoided in certain degree. Besides that, the most attracting feature of our proposed algorithm is that the quality of fused image can be adjusted freely through controlling the approximation error, and the fusion image has good robustness to the noise in source images. This feature can help us to preserve main features of source images in the fused image and ignore some unimportaint details.

II. ORTHOGONAL MATCHING PURSUIT

In this section, we provide a basic description about the orthogonal matching pursuit, an algorithm for sparse representation. Firstly, suppose that $\mathbf{x}$ is an arbitrary signal in R^n, and let $\{\mathbf{d}_1, \mathbf{d}_2, \cdots \mathbf{d}_k\}$ be a family of k vectors, named as the redundant dictionary. Form a $n \times k$ matrix $\mathbf{D}$ whose columns are the vectors in the dictionary.

The OMP algorithm aims to approximate the solution of one of the two following problems, the sparsity constrained problem solving by

$$\hat{\boldsymbol{\alpha}} = \arg\min_{\alpha} \|\mathbf{x} - \mathbf{D}\boldsymbol{\alpha}\|_2^2, \text{ subject to } \|\boldsymbol{\alpha}\|_0 \le K \tag{1}$$

Or the error constrained problem solving by

$$\hat{\boldsymbol{\alpha}} = \arg\min_{\alpha} \|\boldsymbol{\alpha}\|_0, \quad \text{subject to } \|\mathbf{x} - \mathbf{D}\boldsymbol{\alpha}\|_2^2 \le \varepsilon \tag{2}$$

Here, the notation $\|\boldsymbol{\alpha}\|_0$ stands for the nonzero entries in the vector $\boldsymbol{\alpha}$.

The greedy OMP algorithm selects the atom with the highest correlation to the current residual at each iteration. Once the atom is selected, the signal is orthogonally projected to the span space of the selected atoms and the residual will be recomputed. The above procedure repeats until the stopping criterion is satisfied.

Algorithm Orthogonal Matching Pursuit

Require: Dictionary $\mathbf{D}$; Signal $\mathbf{x}$; sparsity K or error ε

1. Initialize the residual $\mathbf{r}_0 = \mathbf{x}$, the index set $\Lambda_0 = \varnothing$ and the iteration counter $i = 1$.
2. Find the index λ_i that solves the following

optimization problem.

2. $\lambda_i = \arg\max_{j=1,2,\cdots k} \left| \mathbf{d}_j^T \mathbf{r}_{i-1} \right|$

3. Augment the index set. $\Lambda_i = \Lambda_{i-1} \cup \{\lambda_i\}$

4. Solve a least-squares problem to obtain a new signal estimate:

   $$\boldsymbol{\alpha}_i = \arg\min_{\alpha_i} \left\| \mathbf{D}_{\Lambda_i} \boldsymbol{\alpha}_i - \mathbf{r}_i \right\|_2$$

5. Calculate the new residual: $\mathbf{r}_i = \mathbf{r}_{i-1} - \mathbf{D}_{\Lambda i} \boldsymbol{\alpha}_i$

6. Increment the iteration counter i and return to the step 2 if the stopping criterion isn't met.

III. FUSION SCHME

The fusion framework of the IFOMP algorithm is illustrated in Fig.1. Firstly, the two source images are decomposed by two-scale laplacian pyramid transform respectively. For the low frequency components of the images, the fuse rule of weighted average and energy selection scheme proposed by Burt[7] is adopted. For the high frequency components of images at different scales, we choose the OMP fusion scheme.

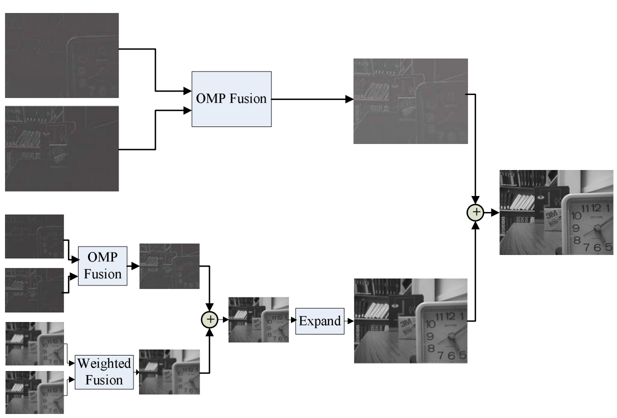


Figure 1. Fusion framework using OMP

The algorithm used to implement the OMP fusion of details images is described as following:

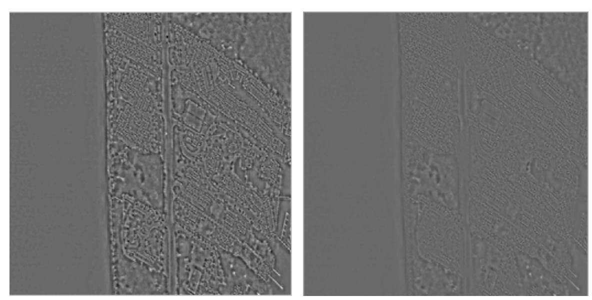
Step 1: choose a group of images containing similar content with source images, and subtract a certain number of image blocks of same size *N*x*N*. Assuming that each image block is represented by a vector $\mathbf{x} \in R^n$ ($n = N^2$), a redundant dictionary $\mathbf{D} \in R^{n \times k}$ can be trained through K-SVD algorithm[8].

Step 2: Suppose source images A and B are pair of detail images at the same scale and F is the fused result. Source images are divideded into every possible small *N*x*N* image patches, ordered lexicographically as column vectors $\mathbf{x} \in R^n$ .Using the OMP algorithm, the image patch can be represented by the linear combination of few vectors from the dictionary $\mathbf{D}$. The solution of the equation (1) is very sparse indeed, $\|\boldsymbol{\alpha}\|_0 << n$ .These few vectors reflect the main features, such as edges or contours in the image patch,which are most sensitive information to the human visual system.Therefore, the approximation of image patches can be gained by

$$\mathbf{x}_A \approx \mathbf{D}\boldsymbol{\alpha}_A \quad (3)$$

$$\mathbf{x}_B \approx \mathbf{D}\boldsymbol{\alpha}_B \quad (4)$$

During the OMP algorithm, the stop condition of iteration procedure is based on the energe of the residual. When the energy of the residual image reaches the criterion $nC^2(n)\varepsilon^2$ (C is a parameter depending on *n*, and ε is approximation error), the OMP will stop. In this way, all image blocks will have roughly similar approximation error. But in fact, some blocks may still exist some dicsernable structures compared to other blocks at the same approximation error. So another stopping criterion named as coherent ratio $CR_i = \delta_i^2 / \delta_{i-1}^2$ (δ_i^2 is the variation of residual block at the *i*th iteration , $0 < CR < 1$) is introduced here. If CR_i is beyond the cohere ratio threshold T_{CR} , it means there are no more interesting features left in the residual block and the OMP algorithm can stop. Fig.2 shows the residual images comparision using above two stopping criterions separately. Obviously, more features are extracted from source image using new criterion.



(a) $\varepsilon = 3$ (b) $T_{CR} = 0.9$

Figure 2. Residual images using two different stopping criterions

Step 3: image fusion is performed in the OMP domain. The method $g(\cdot)$ that combines the atom coefficients matrixes is called "fusion rule".

$$\boldsymbol{\alpha}_F = g(\boldsymbol{\alpha}_A, \boldsymbol{\alpha}_B) \quad (5)$$

Many different fusion rules have been proposed in the literature. Here the common rule "max-abs" is applied simply. Once the coefficients matrix $\boldsymbol{\alpha}_F$ is constructed in the OMP domain, we can move back to the spatial domain by following equation:

$$\mathbf{x}_F = \mathbf{D}\boldsymbol{\alpha}_F \quad (6)$$

Step 4: Considering image patches are overlapped, all reconstructed image blocks should be averaged to gain the fusion image F at last.

IV. EXPERIMENTAL RESULTS

It is impossible for us to execute an exhaustive comparision with many different fusion methods exist in literatures. In order to test the performance of the proposed IFOMP algorithm, instead we compared our results with traditional wavelet fusion[9] on three groups of images such as multi-focus images, hyper-spectral images, and infrared and visual images. The wavelet fusion method uses Bior. 9/7 wavelet and three scale decomposition.

Fig.4 shows the fusion result of the multi-focus images. As we can see, the visual quality of Fig.4(d) is much better than that of Fig.4(c). Through careful respection, the IFOMP fusion result contains more geometry structures and sharp edges, for example, the disks on the table or the books on the shelf.

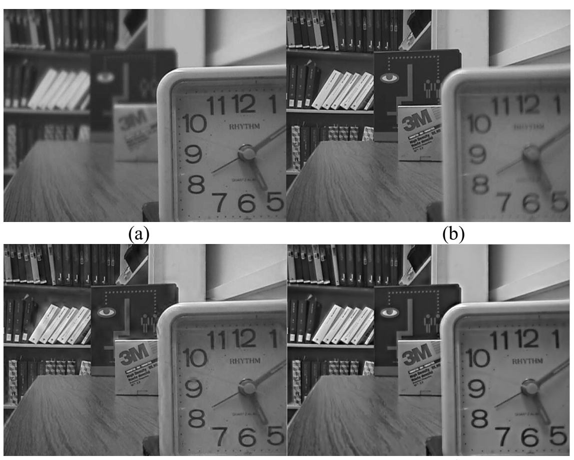


Figure 3. Fusion of multi-focus images(640×480) (a)focus on the left. (b) focus on the right. (c) wavelet fusion. (d) IFOMP.

Fig.5(a) and Fig.5.(b) are two hyper-spectral images. In the first image, runways, pipelines and automobiles in the parking place are very clear and impressing. In contrast, buildings and planes are obvious in the second image. The wavelet fusion result showed in Fig5.(c) is really frustrating and disappointing. The artifacts of unexpected aliasing and interference are easily observed around buildings or in smooth regions. In the contrary, the fusion result of our proposed method seems more natural and satisfying. Most of objects can be seen clearly in the fused image.

Another fusion experiment of infrared and visual image is shown in Fig.6. Fig.6(a) is an infrared image and Fig.6(b) is a visual image. Generally, infrared images always include some background noise in certain degree, which may bring troubles to some fusion methods. Compared with other fusion techiniques, the IFOMP algorithm can uncover the underlying inner structures existed in source image and surpress potential noise at the same time. From Fig.6(d), it seems that the fused image created by our method looks sharper and less blurry than that of wavelet fusion, such as roofs, the tower and the car on the street.

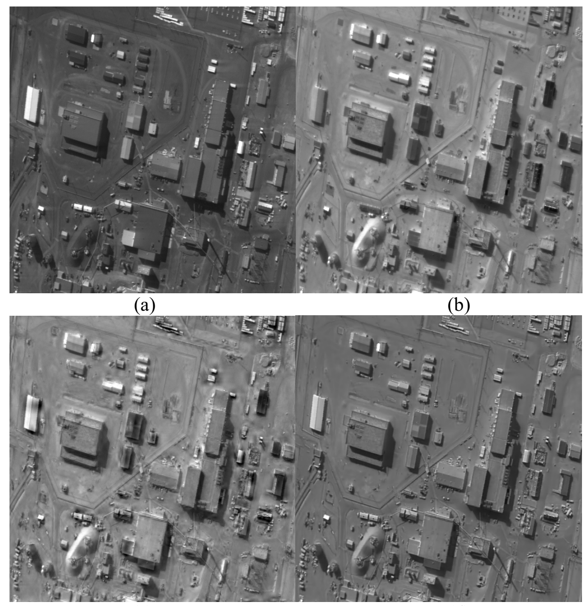


Figure 4. Fusion of hyper-spectral images(512×512) (a)and (b) are hyper-spectral images. (c) wavelet fusion. (d)IFOMP

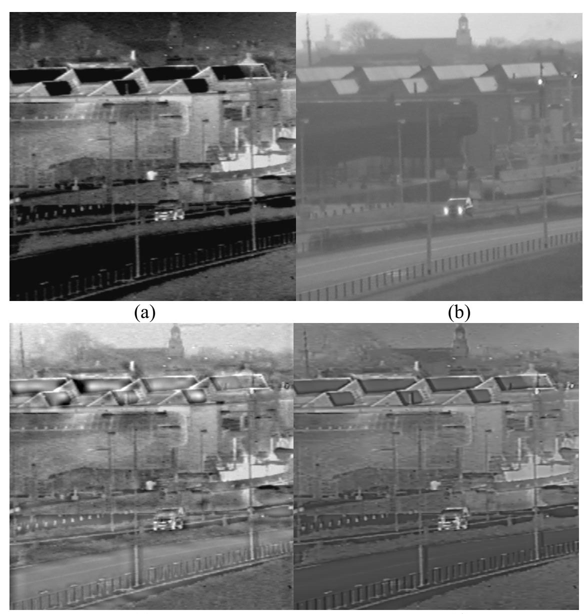


Figure 5. Fusion of infared and visual image(512×512) (a) infared image. (b) visual image. (c) wavelet fusion. (d) IFOMP.

In order to evaluate the fusion performance more objectively, three metrics are considered in this paper, which don’t require ground truth images: entropy(H), mutual information(MI) and IQM. Mutual information[10] measures how much information from each source image is transferred to the fused images. The final metric IQM[11], presented by Piella and Heijinmans, is based on an univeral image quality metric[12] which computes the similarity of local structure information. For these metrics, larger value indicates better fusion quality. From Tab.1, we can observe that the MI and IQM of the IFOMP algorithm outform that of wavelet fusion method, except the entropy. This is due to approximation scheme of the IFOMP algorithm, which may cause some unimportant information lost in the fusion result.

TABLE I. COMPARISON OF IMAGE FUSE RESULTS

Image Types	Methods	H	MI	IQM
multi-focus images	Wavelet fusion	7.2997	2.575	0.9948
	IFOMP	6.9264	2.898	0.9965
hyper-spectral images	Wavelet fusion	6.8390	0.9684	0.9252
	IFOMP	6.4334	0.9727	0.9458
infrared and visual images	Wavelet fusion	7.1350	0.9611	0.7996
	IFOMP	6.7398	1.1295	0.8272

V. CONCLUSIONS

In conclusion, we have proposed a new image fusion method based on orthogonal matching pursuit. Exploiting the orthogonal matching pursuit algorithm, the image features such as geometry structures can be expressed effectively and fused together. Experimental results show that this method performs better in preserving the edge and texture information than that of wavelet fusion. At the same time the algorithm can be straightforwardly extended to handle more than two source images and has wide applications in medical diagnosis and remote sensing.

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