IMAGE FUSION USING PCA IN CS DOMAIN

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ABSTRACT

Compressive sampling (CS), also called Compressed Sensing, has generated a tremendous amount of excitement in the image processing community. It provides an alternative to Shannon/Nyquist sampling when the signal under acquisition is known to be sparse or compressible. In this paper, we propose a new efficient image fusion method for compressed sensing imaging. In this method, we calculate the two-dimensional discrete cosine transform of multiple input images, these achieved measurements are multiplied with sampling filter, so compressed images are obtained. we take inverse discrete cosine transform of them. Finally, fused image achieves from these results by using PCA fusion method. This approach also is implemented for multi-focus and noisy images. Simulation results show that our method provides promising fusion performance in both visual comparison and comparison using objective measures. Moreover, because this method does not need to recovery process the computational time is decreased very much.

KEYWORDS

Compressive Sensing, Image Fusion, Multi-Focus Images, Multi-Focus and Noisy Images

1.INTRODUCTION

The images are the real description of objects. When these images are taken from camera there are some limitations of a camera system. One of which is the limitation of depth of focus. Due to this an image cannot be captured in a way that all of its objects are well focused. Only the objects of the image with in the depth of field of camera are focused and the remaining will be blurred. Fusion can be defined as the process of combining multiple input images into a smaller collection of images, usually a single one, which contains the relevant and important information from the inputs. Nowadays, many well-known fusion algorithms have been proposed [1]. But most of them are based on the whole acquisition of the source images. A work [2] demonstrated the possibility of fusing images without acquiring all the samples of the original images, if the images are acquired under the new technique – compressed sensing.

Furthermore, noise may appear in images during data acquisition. The noise should be removed prior to performing image analysis processes while keeping the fine detail of the image intact. Salt and pepper noise in an image are small, unwanted random pixels in areas where the surrounding majority of pixels are a different value, i.e. a white pixel in a black field or a black pixel in a white field. Many algorithms have been developed to remove salt and pepper noise in document images with different performance in removing noise and retaining fine details of the image[3]. Median filter is a well known method that can remove this noise from images [4]. The removal of noise is performed by replacing the value of window center by the median of center neighborhood.

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Compressed sensing is a new rapidly growing research field emerging primarily in the USA, which investigates ways in which if you acquire a signal in some basis that is incoherent with the basis in which you know the signal to be sparse in, it is very likely you will be able to reconstruct the signal from these incoherent projections. The image data can be mapped to a sparse vector via a sparsifying transform. Different types of images have sparse representations under different transforms. Images are known to have a sparse representation in the FFT, DCT and wavelet transform domain.

The DCT has the property that, for a typical image, most of the visually significant information about the image is concentrated in just a few coefficients of the DCT. It is an orthogonal transform, which has a fixed set of basis functions, an efficient algorithm for computation, and good energy compaction and correlation reduction properties. The DCT is a real valued transform and is closely related to the DFT. In particular, a N ×N DCT of x(n1,n2) can be expressed in terms of DFT of its even-symmetric extension, which leads to a fast computational algorithm. Additionally the computation of the DCT requires only real arithmetic. Because of the above properties the DCT is popular and widely used for data compression operation.

Regarding image fusion in CS, one natural way is to fuse the images after being reconstructed from the random projections which is called fusion-after-reconstruction (FAR) method. However, in order to reduce the computational complexity and to save storage space, a better way is to directly combine the measurements in the compressive domain, and then to reconstruct the fused image from the fused measurements. There are several different methods which have been proposed (e.g. a simple maximum selection fusion rule [2], a weighted average based on entropy metrics of the original measurements [5], Han's method [6]). In [6], a random measurement matrix (with size $M \times N$)acquired from the sampling filter by using nearest neighbor techniques is used to obtain compressed measurements (with size $M \times 1$). In this paper, Sampling is performed on multiple input images by using a DCT-based sampling model to obtain the compressed measurements with size $n \times n$. Inspired by PCA fusion method, fused image acquires from these measurements directly, but in [6], the recovery algorithm total variation minimization [9] is used to obtain the fused image. This our method also is implemented for multi-focus and noisy images. A bout them, salt and pepper noise is removed from input images by using median filter and then this proposed sampling model is applied to acquire compressed measurements and our fusion method is done similar to before. At the end, wiener filter is exerted to the fused image.

2.COMPRESSED SENSING

In this section we present a brief introduction to the Sparse model and compressive sensing background. Consider a real-valued, finite-length, one-dimensional, discrete-time signal X , which can be viewed as an N × 1 column vector in R^N with elements x[n], n = 1, 2, . . . , N. Any signal in R^N can be represented in terms of a basis of N × 1 vectors $\{\psi_i\}$. For simplicity, assume that the basis is orthonormal. Using the N × N basis matrix $\psi = [\psi_1 | \psi_2 | ... | \psi_N]$ with the vectors $\{\psi_i\}$ as columns, a signal X can be expressed as

$$X = \psi S \quad \text{or} \quad X = \sum_{i=1}^{N} S_i \psi_i \qquad (1)$$

Where S is the N × 1 column vector of weighting coefficients $S_i = \langle X . \psi_i \rangle = \psi_i^T X$ and $.^T$ denotes transposition. Clearly, X and S are equivalent representations of the signal, with X in the time or space domain and S in the ψ domain.

The signal X is K-sparse if it is a linear combination of only K basis vectors, that is, only K of the S_i coefficients in (1) are nonzero and (N − K) are zero. The case of interest is when K<< N. The signal X is compressible if the representation (1) has just a few large coefficients and many small coefficients [7].

The digital image "Lena" and its frequency transform are shown in Fig. 1.

Figure 1. (a) Original image. (b) Its DCT

The DCT relocates the compact energy in the upper left corner of the image [8]. Lesser energy or information is distributed over other areas, as shown in Fig. 1 (b). The image is converted to a sparse vector in DCT domain. Most information of the original image is concentrated statistically in just a few large coefficients, while most of the high frequency coefficients are either zero or close to zero[6].

3.IMAGE FUSION METHOD

3.1. Sampling

Most of the energy of a digital image concentrates at low frequencies (upper left corner shown in Fig. 1(b)). So we choose the sampling model which contains radial lines extending from the upper left corner to the other side of an image, as shown in Fig. 2. Consequently, most low frequency information of image that is located at the upper left corner in the DCT domain, preserves with this sampling filter.

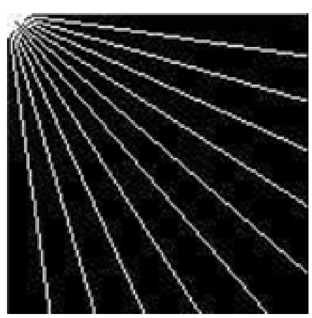

Figure 2. DCT based sampling filter

3.2. Fusion

we explain our method for two input source images, then we can generalize it for multiple input images. According to Fig. 3, we compute two-dimensional discrete cosine transform of two input images and then these measurements are multiplied with sampling filter, so compressed images are obtained. we take inverse discrete cosine transform of them.

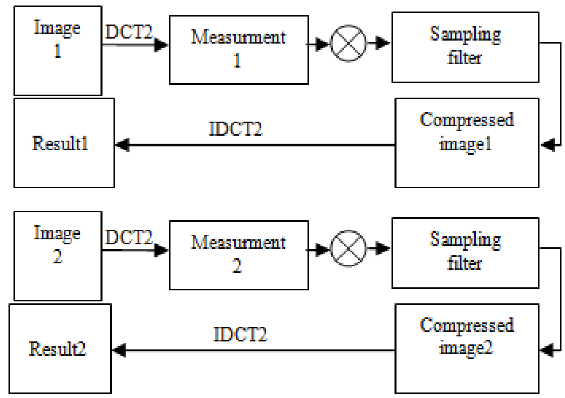

Figure 3. Block diagrams of computing two compressed results

PCA is a statistical method for transforming a multivariate data set with correlated variables into a data set with new uncorrelated variables. For this purpose search is made of an orthogonal linear transformation of the original N-dimensional variables such that in the new coordinate system the new variables be of a much smaller dimensionality M and be uncorrelated. In the Principal Component Analysis (PCA) the sought after transformation parameters are obtained by minimizing the covariance of error introduced by neglecting N-M of the transformed components.

So by using PCA fusion method, fused image achieves from these results as shown in Fig. 4

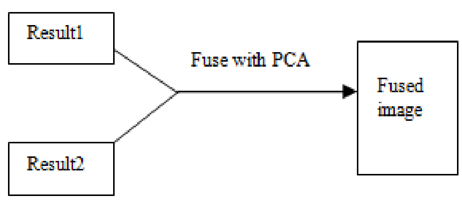

Figure 4. Block diagram of computing fused image

4.SIMULATION AND EXPERIMENTAL RESULTS

4.1. Multi-Focus Images

Two sets of images are employed for performance Evaluation. In this section, different methods are tested and compared with our method.

In the first group, the comparison is performed on a pair of multi-focus images with size of 512*512 and in the second group, multi-modal medical images supplied by Dr. Oliver Rockinger [10] are used as input.

As shown in Fig. 5, our method provides visually natural fused image and does not introduce any noticeable artifacts. Also it contains most of the details of the individual input images in Fig. 5(b) and Fig. 5(c).

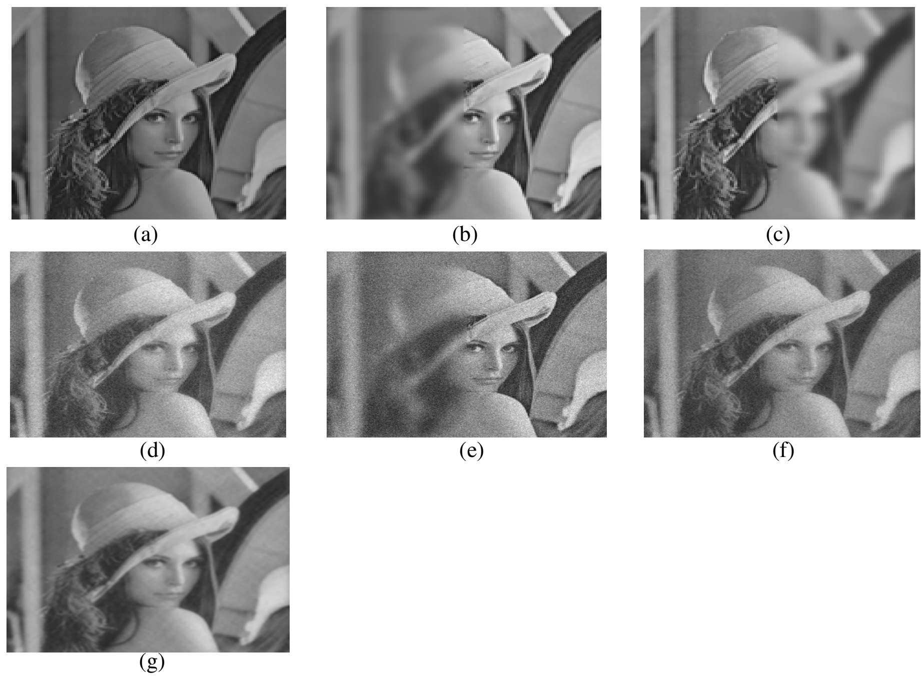

Figure 5. (a) Reference image. (b) Focus on the left part. (c) Focus on the right part. (d) Fusion result by FAR method. (e) Fusion result by DS_MS method [2]. (f) Fusion result by Han's method [6]. (g) Fusion result by our method

With regard to the visual comparison of the second group, the fusion result by using our method in Fig. 6 (f) contains more information than the input images in Fig.6 (a) and (b).

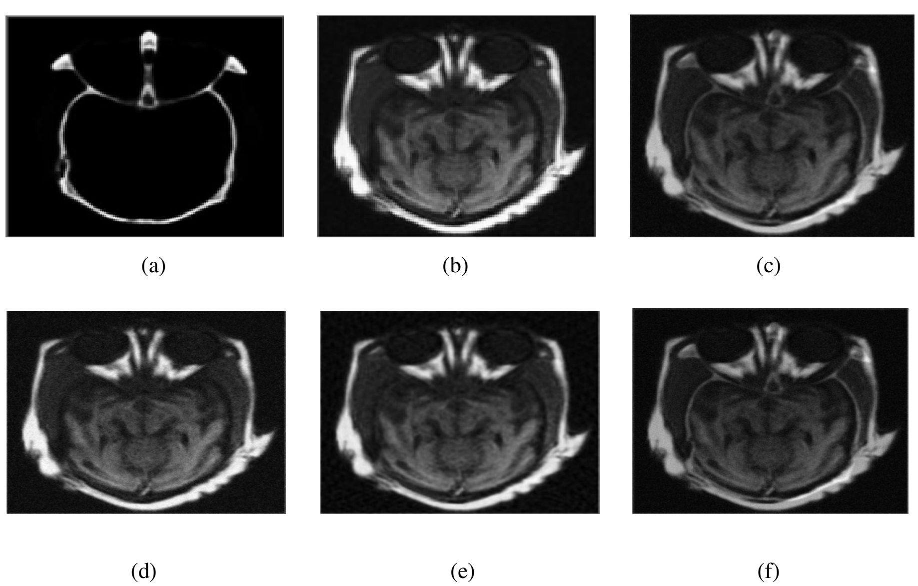

Figure 6. (a) CT image. (b) MRI image. (c) Fusion result by FAR method. (d) Fusion result by DS_MS method [2]. (e) Fusion result by Han's method [6]. (f) Fusion result by our method

In addition to visual comparison, we also present fusion results with three objective metrics [11]: information entropy(IE), the average gradient (AG) of fused image, and the mutual information (MI) between image.

Table 1. Quantity Evaluation of Reference Image (Lena)

IE	AG
7.0880	3.7965

Table 2. Quantity Evaluation of First Group

Methods	IE	MI	AG
FAR	7.3979	2.7570	9.2010
DS_MS	7.3414	2.3026	10.3900
Han’s method [6]	7.2896	2.7551	8.5384
Our method	7.2492	4.7737	1.8260

It is shown in tables (1) and (2) that our method outperforms the other methods in terms of AG, IE and MI. AG and IE values are near to the actual values. Also the larger values of MI imply better image quality which means that the fusion result of our method contains more details than those of the other methods.

Table 3. Quantity Evaluation of Second Group

Methods	IE	MI	AG
FAR	6.7970	2.4079	4.5971
DS_MS	7.0219	2.1827	6.7127
Han’s method [6]	6.6686	2.3233	4.3460
Our method	6.9052	3.4140	3.1371

It can be seen easily that our method performs better than others when comparing the AG and MI, though IE value for DS_MS is a bit larger than that for our method. DS_MS method [2] uses a “double-star’’ sampling pattern in CS and a maximum selection fusion rule.

Overall, based on the visual comparison and comparison using objective measures, we can draw the conclusion that our method achieves better performance than others.

4.2. Multi-Focus And Noisy Images

Salt and pepper noise is a form of noise typically seen on images. It represents itself as randomly occurring white and black pixels. An effective noise reduction method for this type of noise involves the usage of a median filter. So at first, we use this filter for removing salt and pepper noise from input images and then we apply our new fusion method to acquire fused image. Finally, wiener filter is used for removing the rest of noise in the fused image. It is a type of linear filter, tailoring itself to the local image variance. Where the variance is large, wiener performs little smoothing. Where the variance is small, wiener performs more smoothing. It often produces better results than linear filtering. The adaptive filter is more selective than a comparable linear filter, preserving edges and other high-frequency parts of an image. This procedure is done with other methods. Results are shown below.

Figure 7. (a) Reference image. (b) Source image1: Right part of image has salt and pepper noise and the left part of it is blured. (c) Source image 2: Left part of image has salt and pepper noise and the right part of it is blured. (d) Result image with FAR method. (e) Result image with DS_MS method [2]. (f) Result image with Han's method [6].(g) Result image with our method.

In the visual comparison, we can realize that (g) has a better performance in clarity, contrast and preservation of details than (e) and (f).

Also we calculate three objective metrics for result images: information entropy(IE), the average gradient (AG) [6], and the signal to noise ratio (SNR).

(a) Image entropy (IE) :

This metric measures the image complexity, where entropy is defined as:

$$Entropy = -P \log(P) \qquad (2)$$

P is the estimated probability density function of the selected image region.

(b) Average gradient (AG) :

The average gradient is a measure of contrast in a image. It is commonly used to evaluate the clarity of image. We use average gradient as a criterion for image fusion quality. The greater the average gradient value is, the sharper is the image. It can be calculated as:

$$\bar{g} = \frac{1}{n}\sum \sqrt{\frac{(\Delta I_x)^2 + (\Delta I_y)^2}{2}} \qquad (3)$$

where n is the size of the image, ΔI_x and ΔI_y are the differences in horizontal and vertical direction respectively.

(c) Signal to noise ratio (SNR) :

$$P = \sum_{i=1}^{M}\sum_{j=1}^{N}(S(i,j))^2 \qquad (4)$$

$$N = \sum_{i=1}^{M}\sum_{j=1}^{N}(A(i,j) - S(i,j))^2 \qquad (5)$$

$$SNR = \frac{P}{N} \qquad (6)$$

where A is the source image and S is the fused image. Size for source and fused images is $M \times N$.

Table 4. Quantity Evaluation of Reference Image (Barbara)

IE	AG
7.6258	8.6036

Table 5. Quantity Evaluation of Images(Barbara)

Methods	IE	AG	SNR
FAR	7.5273	3.5500	10.9235
DS_MS	7.3362	3.5461	3.7172
Han's method [6]	7.3831	3.2207	4.0867
Our method	7.5405	2.8827	4.9622

Attending to tables (4) and (5), we can conclude that our method outperforms than others (except FAR) in terms of IE and SNR. The AG and SNR values for FAR method are better than ours. However, our method only needs half of the computation and half of the data to be transmitted.

In one word, considering the qualitative analysis and the quantitative evaluation, we conclude that results of our method are superior when compared to others.

5.CONCLUSION

In this paper, we present a new image fusion method based on the CS theory and compare it with other methods. Our method is done on blurred images. Visual analysis and the quantitative evaluation show our fusion method performs better than others. For blurred and noisy images, first salt and pepper noise is removed from images ,then our fusion method is applied on them. Finally, wiener filter minimized variation the pixel value. In this case, also, we achieve better performance with this new fusion method.

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