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Effective Denoising of Hyper Spectral Images Using Block Matching Transform Based Technique

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Abstract*—Hyper spectral images have ample data and lofty spectral resolution which makes its flexible to use in various processing mechanisms like reduction of noise, reduction of dimensionality, image correction and classification. Image denoising is considered to be one of the most paramount processing mechanisms for images. Over the years, with the development of various transform based approaches for denoising of images alms to the literature of digital image processing. In this paper, a block matching transformation technique for effective denoising of hyper spectral imagery is proposed. This paper includes implementation of block matching based denoising using discrete cosine transform. The efficacy of denoising using these transformations is specified in terms of various picture quality indices.

***Index Terms*— Block matching, Denoising, Discrete cosine transform, Hyper spectral image.**

I. INTRODUCTION

The wavelet and contourlet transformations are level dependent which provides very good performance with regard to objective criteria, but fails to preserve and represent certain features of image like edges, singularities etc, so as to overcome those sorts of drawbacks and to further improve the denoising performance criteria regarding hyper spectral images, a block and group dependant transformation is proposed. Block matching transform relies on sparse representation in transformed domain. The improvement of sparsity is accomplished by clustering homogenous segments of the image in to data arrays called groups. The special mechanism that is developed to deal with these sorts of groups is called collaborative filtering [1-5]. With this, three dimensional estimates of the group are obtained which comprises of an array of filtered two dimensional segments or fragments. This helps in getting of finest details of image and preserves the various unique features or characteristics of image. There are various mechanisms or methods by which grouping can be accomplished such as k- means, vector quantization, fuzzy based clustering, self-organizing maps etc [6-8]. The above specified methods make use of high mutual similarity among the data for grouping, which results in making of clusters or groups which are disjoint. The much more effective and simple mechanism for grouping of similar segments or fragments which are not certainly disjoint is referred as matching. Matching is the process of finding the data segments or parts or fragments which are similar to a reference. For suppose, if the similarities among reference and candidate segments are higher than threshold then the block is said to be similar, which helps to constitute a group with similar pixels. There are various distance measuring mechanisms like Euclidean distance, chess block distance, sum absolute difference, normalized distance etc to estimate the similarity between two blocks [9,11,15].

II. BLOCK MATCHING DISCRETE COSINE TRANSFORM

Block matching transform involves two basic steps namely block matching or grouping and 3D collaborative filtering. By block matching mechanism, the blocks that are similar with respect to a reference block are found and are grouped. By collaborative filtering mechanism, two dimensional (2D) estimates are obtained for all the groups and are returned to their original positions or places or locations [13, 16]. Finally aggregation is employed to get the estimate output. In block matching transforms, firstly an image of size $M\ X\ M$ is processed to form three dimensional (3D) groups which is a stacked group of array of blocks of size $k\ X\ k\ X\ l$, where $k\ X\ k$ specifies block size and specifies length of array. Current methodology of block matching transform applies discrete cosine transform on every block in the array and haar transform is going to be applied on all the arrays as third dimension processing mechanism. For example an image of size 512x512 is considered then the three dimensional (3D) groups is formed by stacking up the arrays of blocks of size 64x64x8, where 64x64 specifies the size of every block and 8 specifies the array length. The array of blocks specification is shown in figure 1. In this methodology the basic steps of projection for denoising of images are: grouping mechanism is implemented via block matching, filtering mechanism is implemented by using discrete cosine transform and haar transform followed by threshold and aggregation steps. In this methodology, matching criteria considered is sum absolute difference (SAD) and is represented by:

$$SAD = \sum_{p=0}^{M-1}\sum_{q=0}^{M-1}\left|F(a,b) - F(a+p, b+q)\right| \qquad (1)$$

Where:

$a,b \rightarrow$ *positions of reference block*

$M\ X\ M \rightarrow$ *Size of image*

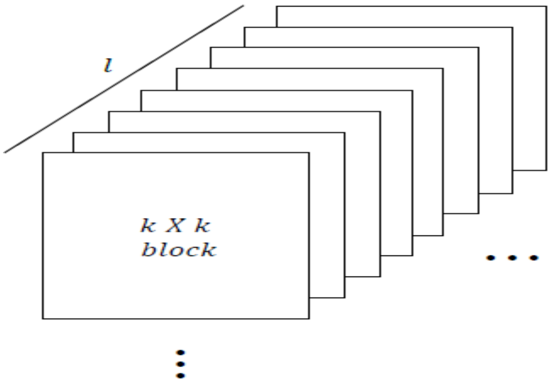

Figure 1: Array of blocks

The block diagram of block matching discrete cosine transform is shown in figure 2.

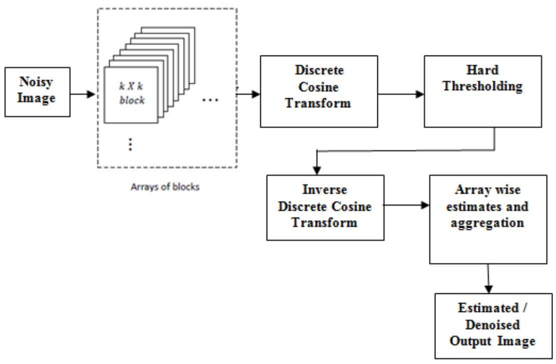

Figure 2: Block diagram of Block matching Discrete Cosine Transform (*for third dimension processing Haar transform is used)

The basic theme behind this sum absolute difference is to find all the blocks similar to reference block $F(a,b)$ with the help of a non sliding window. Once the similar blocks are obtained analogous to reference block and they are grouped to form a three dimensional (3D) array which is denoted as $Z(p,q,l)$.Where:

$p,q \rightarrow$ *rows and columns of every block*

$l \rightarrow$ *length or depth or axis of 3D array*

After performing grouping with block matching then filtering is accomplished with the help of certain transforms like Fourier, Wavelet, Contourlet, Slant, Discrete Cosine, Walsh, Hadamard, Hotelling or KL transforms etc by treating that the noise can also be expressed in the form of sparse representation in transform domain. This means that the transformed coefficients whose absolute value is nearly equal to zero can be treated as noise and can be eliminated with the help of a thresholding or shrinkage mechanism [10,12]. For the purpose of clustering, an efficient and simplest mechanism by name k-means is applied. The basic advantage of this k means clustering mechanism is that it can be easily implementable and has less computational complexities, but it has a limitation that initially the number of clusters needs to be given as a parameter for effective clustering operation [10].

The one dimensional discrete cosine transform can be mathematically expressed as:

$$C(p) = \alpha(p)\sum_{a=0}^{M-1} f(a)\cos\left(\frac{(2x+1)p\pi}{2M}\right) \qquad (2)$$

$$for\ p = 0,1.....(M-1)$$

Where:

$$\alpha(p) = \begin{cases} \sqrt{\dfrac{1}{M}} & for\ p = 0 \\ \sqrt{\dfrac{2}{M}} & for\ p = 1,2,3......(M-1) \end{cases} \qquad (3)$$

The block matching process can be algorithmically specified as follows:

Algorithm: Block matching process

Input: Noisy Image

1. Assign a window size
2. **for** $p = 0\ to\ M-1$ **do**
3. **for** $q = 0\ to\ M-1$ **do**
4. Extract the reference block
5. Obtain all similar blocks
6. Create three dimensional (3D) array
7. **end for**
8. **end for**
9. **return** three dimensional (3D) array

Output: Array of 3D groups

The inverse discrete cosine transform of one dimensional case is mathematically expressed as:

$$f(a)=\sum_{p=0}^{M-1}\alpha(p)C(p)\cos\left(\frac{(2x+1)p\pi}{2M}\right) \quad (4)$$

$$for\ a=0,1,2.....(M-1)$$

The two-dimensional discrete cosine transform can be mathematically expressed as:

$$C(p,q)=\alpha(p)\ \alpha(q)\left[\begin{array}{l}\sum_{a=0}^{M-1}\sum_{b=0}^{M-1} f(a,b)\cos\left(\frac{(2a+1)p\pi}{2M}\right).\\ \cos\left(\frac{(2b+1)q\pi}{2M}\right)\end{array}\right] \quad (6)$$

Where:

$$\alpha(p)=\begin{cases}\sqrt{\frac{1}{M}} & for\ p=0\\ \sqrt{\frac{2}{M}} & for\ p=1,2,3......(M-1)\end{cases}$$

$$\alpha(q)=\begin{cases}\sqrt{\frac{1}{M}} & for\ q=0\\ \sqrt{\frac{2}{M}} & for\ q=1,2,3......(M-1)\end{cases} \quad (6)$$

The inverse discrete cosine transform for two dimensional case is mathematically expressed as:

$$f(a,b)=\sum_{p=0}^{M-1}\sum_{q=0}^{M-1}\left[\begin{array}{l}C(p,q)\cos\left(\frac{(2a+1)p\pi}{2M}\right).\\ \cos\left(\frac{(2b+1)q\pi}{2M}\right)\end{array}\right] \quad (7)$$

For processing of each array haar transform is used. Haar transform is a class of orthogonal matrices which consists of elements 1, -1 or 0 multiplied by a power of $\sqrt{2}$. The haar transform can be represented as: $H_l(z)=H_{p,q}(z)$

$$=\frac{1}{\sqrt{M}}\begin{cases}2^{p/2} & for\ \frac{(q-1)}{2^p}\le z\le\frac{(q-1/2)}{2^p}\\ -2^{p/2} & for\ \frac{(q-1/2)}{2^p}\le z\le\frac{q}{2^p}\\ 0 & elsewhere\end{cases} \quad (8)$$

The three dimensional (3D) array after applying the discrete cosine transform is denoted as $Z^{'}(p,q,l)$ and then thresholding mechanism is applied on the three dimensional (3D) array in order to perform noise suppression. The newly formed array after processing with hard thresholding is denoted as $Z^{''}(p,q,l)$ and then inverse transformation is applied and performed on all blocks and the resultant is expressed as $Z^{\wedge}(p,q,l)$.

The basic steps that are followed for generation of haar basis are as follows:

Step 1: Determine the value of haar basis (M)

Step 2: Evaluate the values of p and q with conditions of:

$$0\le p\le n-1;\ where: n=\log_2 M$$

$$if\ \ p=0\ then\ q=0\ or\ 1$$

$$if\ \ p\neq 0\ then\ 1\le q\le 2^p$$

Step 3: Evaluate the values of *l* and *z* by using:

$$l=2^p+q-1;\ l=0,1,2...............(M-1)$$

The next step to be performed in denoising of images using this approach is to evaluate the estimates of the reference block, which can be accomplished with the help of an averaging filter with various weights that rely on the value of l which are applied on all the coefficients obtained from inverse cosine transform. The above can be mathematically expressed as follows:

$$F(z)=\frac{\sum_{s=1}^{l} f(p,q,l)w_l}{\sum_{s=1}^{l} w_l} \quad (9)$$

All these estimates are aggregated to form the estimated output. Overall framework of image denoising using block matching transform is specified as follows: Finding out of similar blocks with reference to reference block and perform grouping mechanism to get a three dimensional (3D) array. Perform collaborative filtering and get two dimensional estimates of all the blocks by using discrete cosine transform (DCT) and third dimension estimates by using haar transform. Aggregation of these estimates results in denoised image as output.

III. SIMULATION RESULTS

The simulation result of the above specified approach of image denoising is performed in MATLAB. The analyzation of various denoising methods is evaluated by using the data set which is available publicly and normally used by name HYDICE (Hyper spectral Digital Imagery Collection Experiment) data set which has a spatial and spectral resolution of 2 meter and 10 nano meter respectively per picture cell or pixel and covers 210 bands with 400 to 2500 nano meter. The Gaussian noise with noise standard deviation of 20 is considered for evaluation of various denoising strategies and the results are shown in figure 5.

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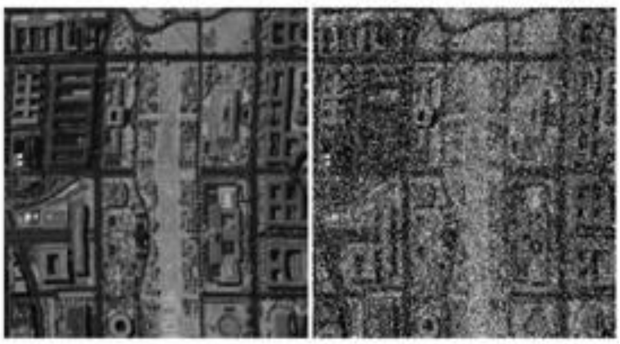
SSIM				
Noise Standard Deviation	**WT**	**ATWT**	**CT**	**BM-DCT**
10	**0.873**	**0.898**	**0.918**	**0.931**
20	**0.817**	**0.836**	**0.869**	**0.913**
30	**0.789**	**0.798**	**0.848**	**0.894**
40	**0.716**	**0.743**	**0.782**	**0.824**
50	**0.679**	**0.711**	**0.763**	**0.812**

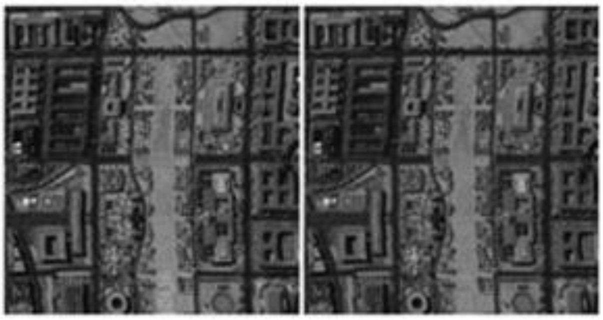
(i)

PSNR (dB)				
Noise Standard Deviation	**WT**	**ATWT**	**CT**	**BM-DCT**
10	**31.22**	**33.35**	**34.36**	**35.95**
20	**29.55**	**31.64**	**32.28**	**32.98**
30	**27.28**	**29.96**	**30.08**	**31.67**
40	**25.96**	**29.22**	**29.54**	**30.02**
50	**24.22**	**27.21**	**28.31**	**29.51**



(ii) **(iii)**

(iv) **(v)**



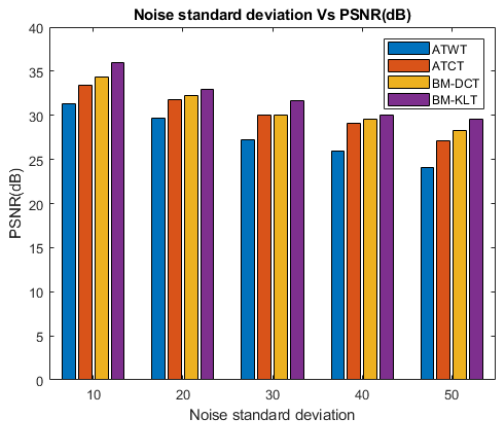
(vi) **(vii)**

Figure 5: Denoising results of the HYDICE dataset of band 65 (i) Original hyper spectral image of band 65 (ii) Original gray image of band 65 (iii) Noisy gray image of band 65 (iv)Wavelet Transform (WT) output (v) Adaptive Threshold based Wavelet Transform (ATWT) output (vi) Contourlet Transform (CT) output (vii) BM-DCT output

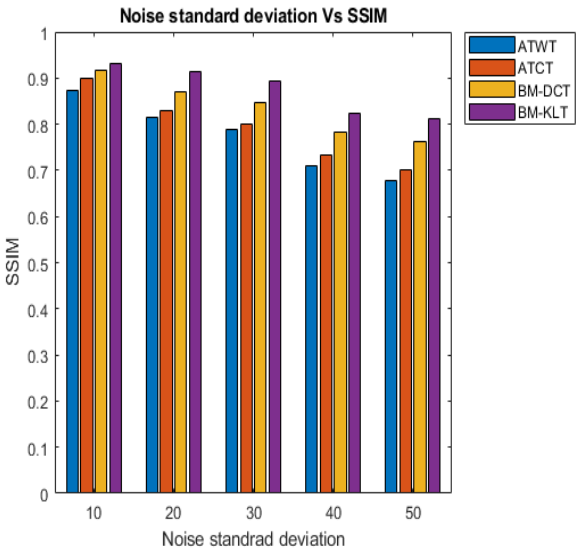
Table 1: Quantitative analysis of PSNR and SSIM evaluation of WT, ATWT, CT and BM-DCT denoising methods

(a) Quantitative analysis of PSNR evaluation

(b) Quantitative analysis of SSIM evaluation



(a) Bar graph representation of PSNR values of denoising results



b) Bar graph representation of SSIM values of denoising results

Figure 6: Bar graph representations of PSNR and SSIM evaluation of WT, ATWT, CT and BM-DCT denoising methods

IV. CONCLUSION & FUTURE SCOPE

The spatial approaches of denoising are cramped as they blur the image during noise removal. Withal, transform domain approaches preserves various details of image perfectly and hence they are quite preferable over spatial methods of denoising. The block matching discrete cosine transform based approach for image denoising are quite efficient and effective because of its features or characteristics like energy compaction, low redundancy, sparseness and small representation of image transformed coefficients. The further research can focus on how to make more accurate patch classification and much more valid depiction of coefficients in transform domain.

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