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Remotely Sensed Image Approximation Using Tetrolet Transform

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ABSTRACT: On expansion, to the remote sensing image, it is troublesome with secure an extraordinary pitiful achieve shortages whether it holds an impressive measure about inconspicuous components. Watched on the two issues, a novel blend framework that is about a percentage sweeping statement will be recommended. The strategy exploitsthose points of interest of the tensor outcome wavelet change over to representational from claiming smooth birch pictures and the capability of the tetrolet change on speak to composition furthermore edge suitably at a similar period. Moreover, two particular techniques for decay need aid designed, which help expanding those vitality focus further what's more preserving the data of the points to the extent that conceivable. The system of the recommended mixture system may be as takes after: to an provided remote sensing image, in those common tensor item wavelet change will be used, then those excess information around contiguous wavelet coefficients is uprooted eventually settling on polyphase decay to each subband,afterward those close estimation of the low recurrence picture cam wood a chance to be got by reconstructing the individuals safeguarded coefficients. Second, to the point by point image, the meagre decay may be conveyed crazy toward that tetrolet change. For those high back subbands, a versatile decay will make accomplished for expanding the vitality amassed.

KEYWORDS: Remote sensing image approximation; sparse representation; tensor product wavelet; tetrolet transform

I. INTRODUCTION

Remote Sensing refers to the branch of science which gets data about items from measurements made from a distance i.e. without actually coming into contact with them. Remote Sensing is the identification of earth highlights by distinguishing the characteristics electromagnetic radiation that is reflected by the earth surface. Every object reflects a portion of electromagnetic radiation incident on it depending upon its physical properties.

In the recent years, wavelets had a developing effect on signal and image processing. The 1-D case, wavelets give optimal representations of piecewise smooth functions. In 2-D, tensor item wavelet bases are imperfect for speaking to geometric structures like edges and surface, since their support is not adjusted to directional geometric properties. Only in case of globally smooth images, they give ideally inadequate portrayals [2]. The 2-D discrete wavelet transform is the most imperative new image compression strategy of the last decade. Routinely, the 2-D DWT is completed as separable transform by cascading two 1-D transforms in the vertical and horizontal direction [6]. The previous decade has seen expanded sophistication and maturity of wavelet-based image compression innovations.

Image sparse representation is to find an effective way of representation that characterizes the significant image features in a compact form. Approximation theory wants to exploit the sparsity of the coefficients. A sparse approximation is a sparse vector that approximately solves a system of equations. Image sparse representation is on the premise that the energy of the image should be concentrated as much as possible. We need sparsity for the purpose of data compression, Image restoration, feature extraction and detection.

Most of the existing image sparse approximation algorithms are not general, they can reach their best approximation performance only under the condition that the image has some certain properties. The tensor product wavelet transform is optimized for presentation of smooth images, directionlets can provide the optimal approximation to cross lines, and wedgelets can detect the line and surface of image effectively, and so on. Therefore, if we want to give a sparse approximation to an image, at first, we should judge whether the image is smooth or rich in details, then adopt a proper sparse approximation algorithm based on the judgment result. If the image is smooth, then the tensor

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product wavelet transform is adopted. If the image is rich in detailed information such as geometric characteristic, edge, and texture, then some directional wavelets can be chosen. It is difficult to determine whether an image is smooth or not, because it is a relative concept. A smooth image also has some detailed information, and an image which is rich in details also has a great deal of low-frequency information, so the sparse approximation algorithm that we chose by the empirical judgment may not be suitable indeed. The best way is to research a relatively common method that has a good ability of sparse approximation to any image, regardless of their characteristics. Remote sensing image has its own unique characteristics, usually contains a large number of ground objects, which causes the information of details is abundant, such as geometric information, edge, and texture information, even the outline of some small targets. Therefore, it is difficult to obtain a good sparse appropriation for the remote sensing image because the coefficients of high frequency subbands are still very large after transformation. Thus, in order to preserve more information of details as much as possible, we have to find a way to increase the ability of energy concentration of high frequency. A reasonable way is to make a further decomposition to those high frequency sub bands in some way.

Method uses the tetrolet transform for sparse image estimate, which is a kind of locally adaptive Haar wavelet transform. The tetrolet transform is practically not affected by the Gibbs wavering in light of the fact that the bolster area of it is little, so it can keep the bearing of the edge and surface of an image very effectively [1]. Moreover, compared with other directional wavelets which usually focus on given geometric structure, the tetrolet transform can give great approximations to an assortment of geometric structures.

II. PROPOSED SYSTEM

This method uses for remote sensing image approximation which adopts the usual tensor product wavelet transform to approximate the low frequency of the original image and uses the tetrolet transform which can give an effective representation of edges and texture to approximate the detailed image. In order to provide a better sparse approximation performance and preserve more information of details at the same time, two specialized processes of decomposition for further energy concentration are performed in two stages.

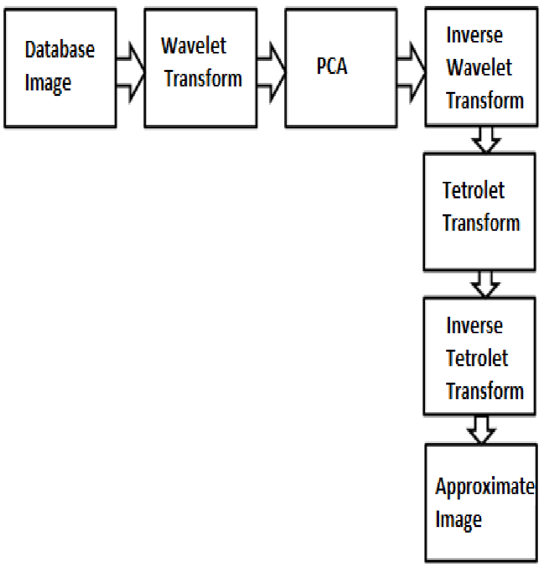

Fig. 1. Overall framework of the method

Based on the overall framework shown in Figure 1, for a given remote sensing image, the sparse approximation can be carried out by two stages as shown in Figure 2.
Stage 1 provides a sparse approximation of low frequency image.
Stage 2 provides a sparse approximation of the detailed image.

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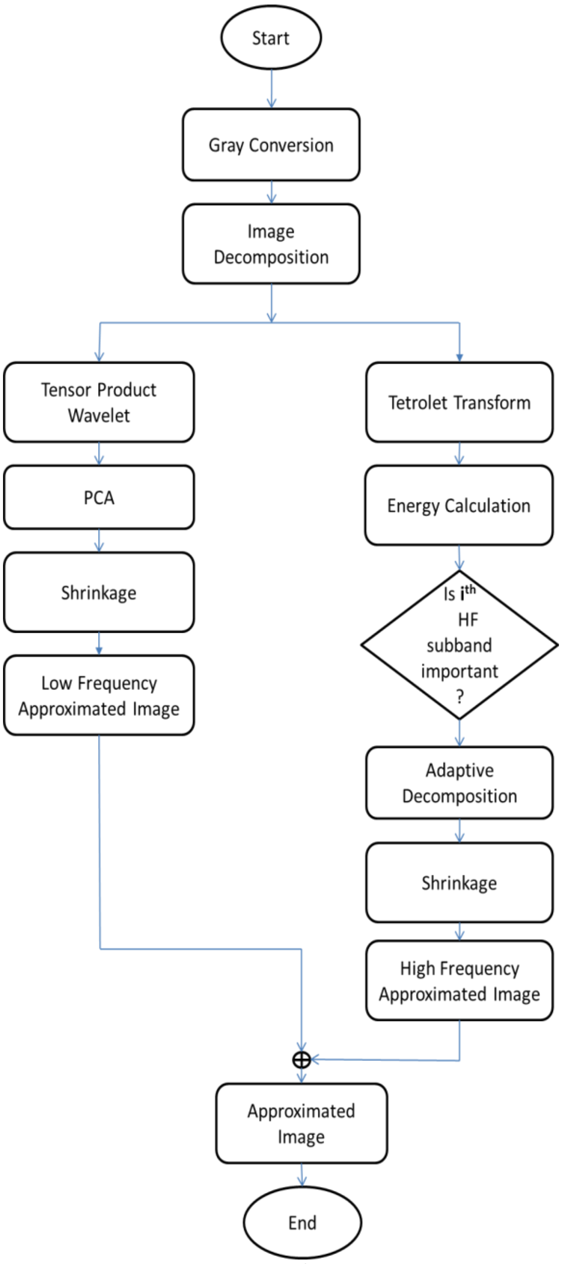

Fig. 2. Flowchart of the algorithm

A. Sparse Approximation of the Low-Frequency Image

Tensor-Product Wavelet Transform:

For some applications, considering the symmetry and perfect reconstruction characteristics, two wavelets can be chosen. One is used to decompose and the other to reconstruct. This kind of wavelet is called biorthogonal wavelet for the reason that both of them must satisfy the condition of orthogonality.

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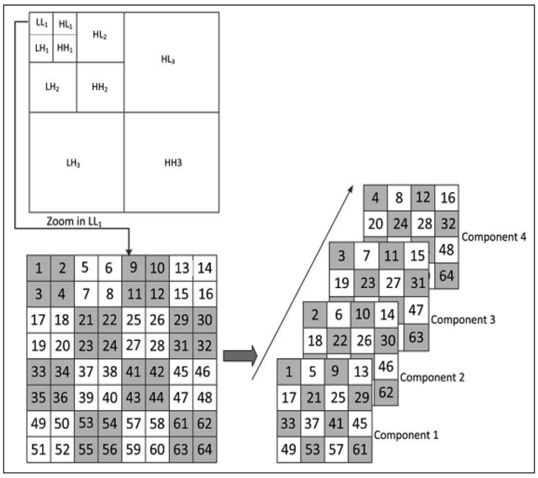

Fig. 3. Polyphase decomposition process of each subband

The polyphase decomposition process is a process that split wavelet coefficients in a subband and regroups them again. The splitting process can be realized by the p-fold filter, which divides the adjoining wavelet coefficients into successive elements. Suppose each subband is divided into four components. In order to eliminate the redundancies between adjoining wavelet coefficients, it is divided into many non-overlapping blocks, different colors used to represent different blocks. The digit of each block represents the position of coefficient.

The flowchart of this algorithm is shown in the Figure 2. First, the tensor product wavelet transform is applied to the original remote sensing image. In order to remove the redundancies between adjoining wavelet coefficients localized in a same subband, make polyphase decomposition to each subband with a p-fold filter and many components can be obtained, PCA is used to eliminate the redundancies between components, so that energy must be further concentrated. As a result, it can provide a better performance of sparse. Shrinkage procedure is applied to preserve the larger coefficients.Finally, the inverse tensor product wavelet transform is conducted, so the approximation of the low-frequency image can be obtained.

B. Sparse Approximation of the Detailed Image

Tetrolet Transform:

The concept of “Tetrominoes” was introduced by Golomb. They are some shapes that are formed by a union of four unit squares. Without considering rotations and reflections, there are five different shapes, as shown in Figure 4. It is obvious that each block whose size is N×N can be covered by tetrominoes if and only if N is even. The core idea of tetrolet transform is to allow more general partitions such that the local image geometry is considered, i.e., use the tetromino partitions.

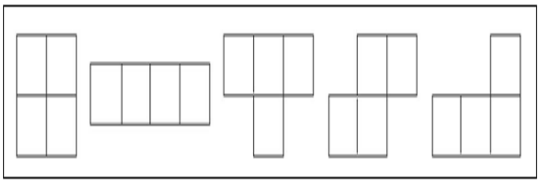

Fig. 4. Five free tetrominoes

The detailed image of the original image has been obtained from the original and lower approximated image which is rich in edges and texture can be obtained. The sparse approximation of the detailed image will be performed by the tetrolet transform because it can preserve the edge and texture information effectively.

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The flowchart of this algorithm is shown in the Figure 2.At first, the image is decomposed by tetrolet transform. Following, a process of adaptive decomposition is conducted on those high-frequency subbands.

Algorithm is described as follows:
a) Tetrolet Transform for the DetailedImage:
1) Divide the detailed image into 4×4Blocks.
2) For each block, we consider the admissible tetromino = 1,…,117 coverings.
For each tiling c, we apply the haarwavelet transform to the four tetromino subsets. Then, the 4 low-pass coefficients and 12 tetrolet coefficients for each tiling are obtained.
They can be obtained from the Haar wavelet transform matrix.
Choose the covering c* that corresponding to the l1 –norm of the 12 tetrolet coefficients is minimal.
For each block, the optimal decomposition can be obtained.
In order to make further decomposition using the tetrolet transform, rearrange the entries of the vectors and into
2×2 matrix using a reshape function.
After finding the sparsest tetrolet representation in each block, we store the high-pass matrices and the optimum
covering.
Apply step 1) to step 5) to the low pass part, until the decomposition level reaches to J.

b) Adaptive Decomposition of High-Frequency Subbands:
For the detailed image, after the tetrolet transform, there is still a lot of useful information in high-frequency subbands due to the unique characteristics of the remote sensing image. If a high-frequency subband is judged to be important according to the energy of that subband, then it will be decomposed continually by tetrolet transform. Certainly, there must be some limitations to the decomposition level of a subband. After the adaptive decomposition process of high-frequency subbands, most of the energy of the detailed image is concentrated on a few coefficients. This is extremely beneficial to retain the information of details. Then, a shrinkage procedure is conducted to preserve the larger coefficients. Finally, the inverse tetrolet transform and the process of merge are applied based on the procedure in Algorithm. As a result, the approximation of the detailed image is obtained which contains most of the edge and texture information. Based on the result, the approximation image of the original image can be obtained.

III. Simulation Results

Remotely sensed image here landsat database is used as input image whose resolution is 5494*5839 and size is 39.1 MB which is processed by using MATLAB and image processing toolbox. Fig. 5. shows the original image as the input image for performing operations on it. Original image is resized for the pre-processing purpose as shown in fig. 6. Input image is colour image which converted into gray scale as shown in fig. 7. for processing on it. Input image is decomposed using 9/7 biorthogonal filter for low frequency approximation and reconstructed image is as shown in fig. 8. Detailed image is obtained by taking difference of original image and low approximated image shown in fig. 9. Detailed image is decomposed by using Tetrolet transform and resulted image shown in fig. 10. Original image size (fig. 5.) is 39.1 MB and output image is of 66.3 KB with PSNR 53.03 and RMSE 0.0569. After the tetrolet decomposition, resulting image contains high frequency band information. By taking five level adaptive decomposition resulting image is as shown in fig. 11. Different filters applied on output image using top hat and bottom hat filtering. Resulted image is denoised image shown in fig. 12.

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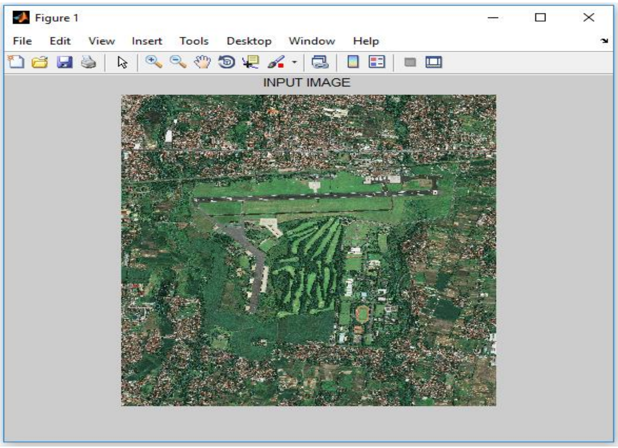

Fig. 5. Original Image

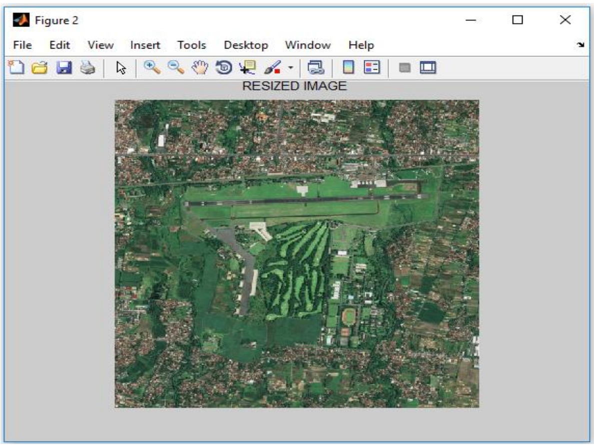

Fig. 6. Resized Image

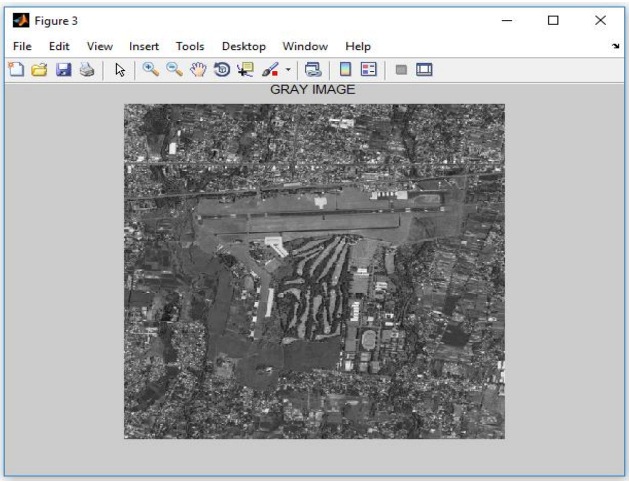

Fig. 7. Gray scale image

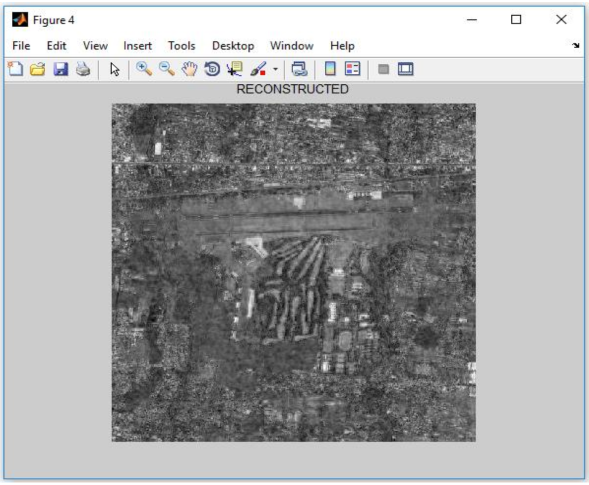

Fig. 8. Reconstructed image

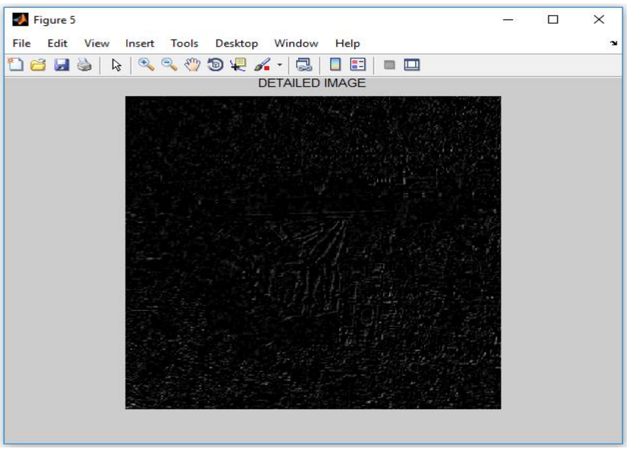

Fig. 9. Detailed image

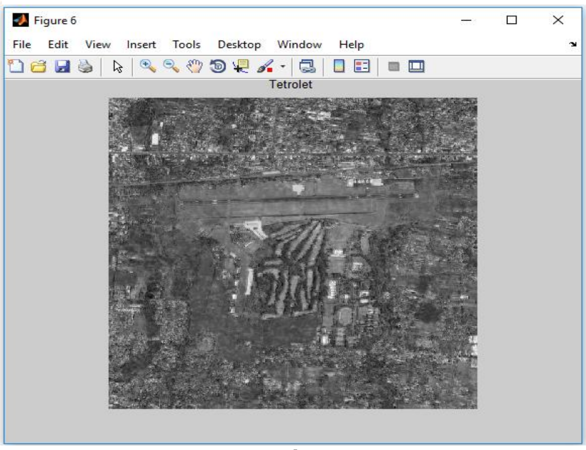

Fig. 10. Tetrolet Image

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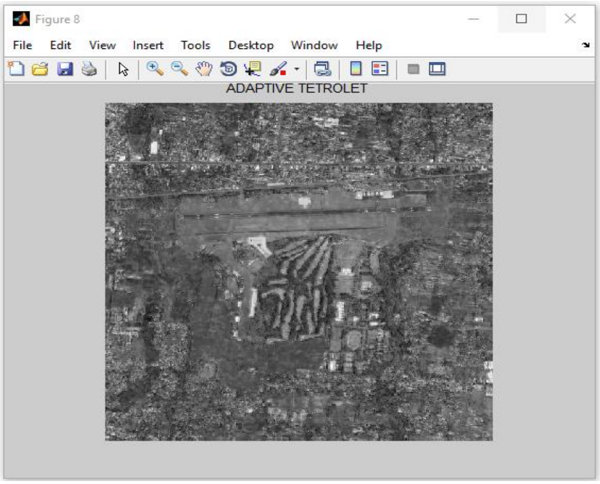

Fig. 11. Adaptive Tetrolet Image

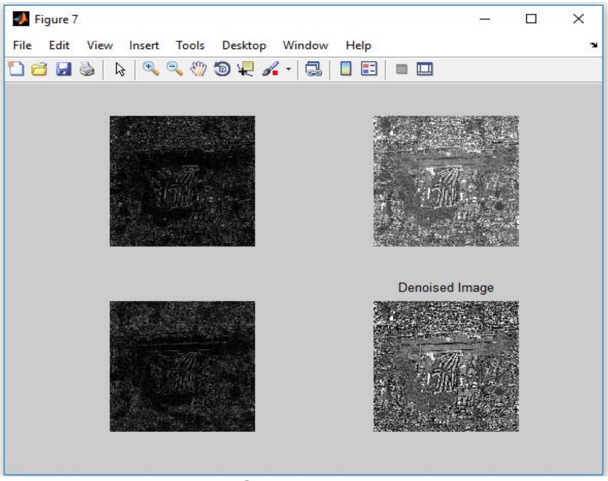

Fig. 12. Denoised Image

Hybrid method results tabulated in Table I indicates that as the size of the input image is larger, lower will be the PSNR and higher will be the RMSE. Original images are sparsely approximated by using hybrid method and resulting images are the approximated images whose sizes are less compared to its original size. Hence image approximation achieved by tetrolet transform is superior.

Table I Database image processed in MATLAB comparison

Database	**Hd1**	**Lunar**	**A1**
RMSE	0.0567	0.0418	0.0502
PSNR	53.054	55.69	54.1189
Original size	39.1 MB	137 KB	158 KB
Output image size	66.3 KB	41.5 KB	46.6 KB

IV. CONCLUSION AND FUTURE WORK

The image approximation method for remotely sensed image is successfully designed using MATLAB. We have obtained direction of edge and texture at the same time. Previous transforms were direction oriented and tetrolet transform is adaptive for any direction as it is less affected by Gibbs oscillations. Quality evaluation index of a tetrolet transform is better than previous transform for remote sensing images. Hence image approximation achieved by tetrolet transform is superior. We can use this method for different types of remote sensing images for various applications.

In future we will focus on the calculation of the ratio automatically. How to allocate the given number of coefficients properly in order to provide a good sparse appropriation while keeping the necessary details at the same time and limitations of the image decomposition levels.

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17.

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