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IMAGE RECOVERY FROM NOISY RANDOM PROJECTION USING DICTIONARY LEARNING TECHNIQUE

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ABSTRACT

An image is nothing more than a two dimensional signal. Digital image processing has very wide applications in almost all the technical fields. The images contain massive data sets and it has to be reduced using dimensionality reduction techniques. But the traditional dimensionality reduction techniques are more expensive. So a new technique has been recently developed known to be random projection method. When compared to the conventional random projection, double random projection gives more accurate results with reduced computational complexity. Recently the images are reconstructed from the double random projected images using both Singular Value Decomposition and Randomized SVD. We experimentally show that more accurate recovery of the image is obtained through rSVD compared to SVD. Often the projected images contain noise during transmission. We also show experimentally that the image can be recovered from the randomly noisy projected images using dictionary learning analysis.

Keywords: double random projection, singular value decomposition, randomized singular value decomposition, dictionary learning.

INTRODUCTION

Processing the massive imagery data sets is often difficult to produce the efficiently useful information. So the massive data sets of images have to be reduced using dimensionality reduction techniques. The dimensionality reduction is just the transformation of a data from a higher dimensional space into a space of fewer dimensions.

Principal component analysis (PCA) was the best and most widely used technique. In PCA the data is projected into lower orthogonal subspace. The lower subspace is obtained by capturing as much of the variation of the data as possible. PCA convert a set of observations of possibly correlated variables into a set of values of linear uncorrelated variables using orthogonal transformations. But it is more expensive in the case of huge data sets like hyper spectral images and thus its use is limited.

Discrete cosine transform (DCT) is much widely used technique for image compression. Since the distortions introduced are at the high frequencies the human eye neglects it as noise. DCT is data independent in contrast to PCA which depends on the eigen value decomposition and thus it is much cheaper compared to PCA and also DCT is much better than PCA compared to the computational complexity and it is thus much widely used.

Many researchers are done in the compressive sensing approach in image analysis. Marcia and Willett [1] developed a new reconstruction method of a super resolution image from a single noisy observation image of low resolution with the design of coded aperture masks. They applied the emerging field of compressive sensing and it is based on the idea that a relatively small number of indirect observations of an image can be used and reconstructs it very accurately when that image is sparse in some basis.

A new sparsity measure of image known as collaborative sparsity [2] was introduced and using this sparsity measure with compressive sensing, the image is reconstructed. Conventional CS recovery methods are based on DCT, wavelet and gradient domain. But in order to achieve a high sparsity domain an adaptive hybrid-space-transform domain is chosen.

But the conventional dimensionality reductions are more computationally difficult and more expensive. The recently developed random projection techniques found its applications mainly in dimensionality reduction and produces more accurate results compared to the conventional methods. The random projection technique is computationally simpler and reduces the dimension of the data set without much significant distortion in the data set.

The random projection technique converts the original high dimensional data into a low dimensional data using the random matrix which can be chosen randomly according to the size of the original image. The recently developed double random projection is more convenient than the conventional random projection techniques which require excessive computational and memory requirements.

The random projection of an image $A \in R^{m \times n}$ can be expressed as

$$B = P^T A \quad (1)$$

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where B represents the projected image and P represents the random matrix used for the projection and $B \in R^{k\times n}$ and $P \in R^{m\times k}$. Thus the image is projected along column which reduces the row dimension. This column wise projection is based on the compressive projection principal component analysis proposed by Fowler [3]. CPPCA is similar to the traditional PCA. In this approach CPPCA projects the data at the encoder and reconstructs at the decoder with an approximation of the principal components with random projections. But later both simultaneous row wise and column wise projection [4] was introduced by Eftekhari, Babaie-Zadeh and Moghddam, i.e.,

$$B = P_1^T A P_2 \tag{2}$$

where P_1 and P_2 are the projected matrices. But all the above methods are iterative techniques.

Thus recently a non-iterative technique is introduced known as double random projection [5]. In this technique both row wise and column wise projection is done, but not simultaneously i.e. one after the other. Before the emergence of image reconstruction only signals were reconstructed from frequency samples [6]. Later researches are done in image reconstruction. The most recent development based on the compressive sensing analysis is discussed in block compressive sensing with land weber reconstruction [7], its multiscale variant [8] and multiple hypothesis prediction [9]. In this paper the original image is reconstructed from the projected images using both SVD and rSVD methods. The rSVD technique was recently used in the case of hyperspectral imaging [10]. SVD is a matrix decomposition method which decomposes the original matrix and rSVD is an approximation of the SVD method.

In this paper, we present the recovery from a projected image which is corrupted with random noise while transmission through the channel. The image is projected and reconstructed using both SVD and rSVD techniques. We have also done a comparative study between the two techniques in this paper. The experimental results show that rSVD is much better. Also we presented the image recovery from randomly projected images corrupted with random noise using dictionary learning analysis.

Thus our paper is organised as follows. Section II presents the methods used for projection, reconstruction and finally how the random noise is removed, Section III gives the experimental results and finally section IV gives a conclusion.

METHOD

For the ease of transmission and processing of image data, the original image is projected. But while transmitting the projected data through the channel it may be corrupted with noise. Since the type of noise cannot be predicted, it has to be removed adaptively. So a new method of reduction of random noise from the projected images is being introduced. After the removal of noise, the original image is being reconstructed. The method for projection, adaptive removal of noise and reconstruction of data are discussed in this section.

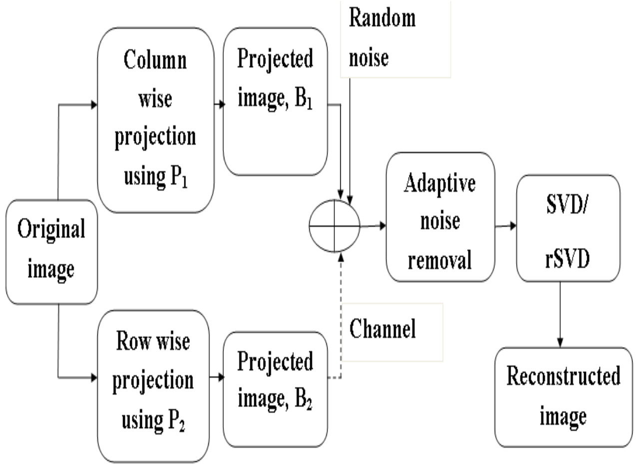

Figure-1. Block diagram.

The image is projected using double random projection and it is reconstructed with the help of SVD and rSVD techniques. The adaptive removal of noise is the main focus in this paper. The techniques used for projection, noise removal and reconstruction are as follows.

Image Projection using Double Random Projection

Double random projection is the most recently developed technique used in projection analysis. Basically the random projection methods are based on randomly selected projection matrices. The matrices are chosen based on the dimension of the original image. Since it is a dimension reduction technique, the projected matrices are of fewer dimensions compared to the original image.

In double random projection, there are two random projections one along the row and the other along the column of the true image. So there is a need of two random projected matrices.

Now consider the original image as $A \in R^{m\times n}$, and the first projection can be made along column with the projection matrix as $P_1 \in R^{m\times k1}$ satisfying $k_1 << m$. Projection along column can be given as

$$B_1 = P_1^T A \tag{3}$$

where $B_1^{k1\times n}$ represents the projected image of A along column. Similarly the projection along row is expressed as

$$B_2 = AP_2 \tag{4}$$

where $B_2^{m\times k2}$ represents the projected image along row using the projected matrix $P_2 \in R^{n\times k2}$ satisfying $k_2 << n$. Thus the image is projected along both column and row. Thus this type of projection helps in the transmission since the data size is reduced and also it is more secure since the projected image is entirely different from the original image. It can be an encrypted version of the image. The main advantage is that only one of the

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projected image and the projection matrix used for the other projection is only required for the reconstruction of the image at the other end.

Adaptive Noise Removal

Noise plays a crucial role in the altering of the image content during transmission through the channel. Since the image has to be transferred more securely without altering the data is not so easy, the noise has to be removed at the receiver end before reconstructing the original image. If the noise is not considered at the receiving end, the reconstruction of the original image from the projected data is impossible. Since the presence of noise makes the projected data more complex, the recovery may not be accurate and cause a drastic change in the recovery.

The noise added to the data during the transmission can be of any type. Thus an adaptive technique has to be introduced. The noise can be taken as random noise which is being entered through the channel. The random noise is removed from the projected data. The recent development in noise recovery from the projected images discusses some particular type of noise such as salt and pepper noise. But in this paper a new technique which can remove any type of noise from the projected images is discussed. Thus the random noise is removed adaptively through the dictionary learning analysis.

In dictionary learning analysis, the projected image let it be B_1 or B_2 can be retrieved based on dictionary data and its coefficient matrix. Due to the addition of noise the projected image becomes Bα and the error can be treated as

$$R = B - B\alpha \quad (5)$$

Where α can be treated as the changes that made to the projected data. Now this new projected image can be represented based on some dictionary data such as Dα I.E.,

$$B\alpha = D\alpha \quad (6)$$

D is the dictionary data that used for the noisy representation of the data and its coefficient matrix is α. Now the difference between the projected image and noisy projected image has to be decremented and it is based on the estimations and updations that made to data entries of D and α.

$$\min \ \|\alpha\|, \quad \text{s.t} \ \| B - D\alpha\| \leq \varepsilon \quad (7)$$

During each updation the error is being reduced and it should be lesser based on the threshold value, ε. Thus any noise entered can be removed based on this approximation technique.

Image Reconstruction

The noise has been removed from the projected images. But still the original image is not yet received. So for the reconstruction from the projected images SVD and rSVD methods are used.

SVD Method

SVD is a matrix factorization method which decomposes the original matrix into three different matrices. Here the SVD is applied to any one of the projected images and it can be either B_1 or B_2. The SVD is only applied after the removal of noise. The SVD of B_1 is computed as,

$$B_1 = USV^T \quad (8)$$

Here U and V are orthonormal matrices and S is the diagonal matrix whose diagonal elements are known to be the singular values of B_1. A low rank-matrix approximation reduces the complexity of finding SVD and selecting only the first columns of V as V_K. This result is applied to (4) as

$$B_2 \approx AV_KV_K^TP_2 \quad (9)$$

$$B_2(V_K^TP_2)^T \approx AV_K \quad (10)$$

Since,

$$A_K \leftarrow AV_KV_K^T \quad (11)$$

where A_K represents low rank approximation of A and thus,

$$A_K \approx B_2\,(V_K^TP_2)^T\ V_K^T \approx AV_KV_K^T \approx A \quad (12)$$

The original image A is reconstructed using SVD technique. But within reduced time more accurate result has to be obtained. Thus SVD technique is approximated into a new method of rSVD which is much faster compared to SVD.

rSVD Method

The computational complexity behind the SVD method leads to the rSVD method which is a randomized matrix approximation method. This technique is more viable and faster than SVD. Consider the column wise projection as in Eq. (3). Then an approximation to the range of A is computed. This is represented as Q with k columns i.e., $Q \epsilon R^{m\times k}$. For the matrix B_2, a target rank k and a oversampling parameter p are chosen randomly satisfying the condition such that the columns of Q should be orthonormal to B_2. Then choose a random test matrix as Ω with $k_2 \times (k+p)$ and generate the matrix product.

$$Y = B_2\,\Omega \quad (13)$$

Then constructed a matrix Q whose columns form an orthonormal basis for the range of Y and then (3) can be written as,
where Q represents matrix approximation.

$$B_1 \approx P_1^T QQ^TA \quad (14)$$

$$(P_1^TQ)^TB_1 \approx Q^TA \quad (15)$$

Then the SVD of $(P_1^TQ)^TB_1$ is computed.

$$(P_1^TQ)^TB_1 = USV^T \quad (16)$$

Thus

$$Q^TA = USV^T \quad (17)$$

Then

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$$A \approx Q\, Q^T A = Q\, (USV^T) \tag{18}$$

So the SVD of A can be approximated as a

$$A = \hat{U}SV^T \tag{19}$$

Where

$$\hat{U} = QU \tag{20}$$

Thus the SVD of the original image A can be generated using the projection image. The original image is reconstructed from the noisy projected images using both SVD and rSVD. Comparing to SVD, rSVD method gives more accurate result in terms of PSNR and also this is much faster than the other.

EXPERIMENTAL RESULTS

The experimental study reveals that the image recovery using the above discussed methods offer better result. The original image as shown in Figure-2 is projected along both row and column using double random projection in Figure-3 and Figure-4. Then the original image is reconstructed from the projected images using both SVD and rSVD techniques as shown in Figure-5 and Figure-6. We have also compared the result with different distributions of Normal, Gaussian and Bernoulli with the projection matrix as shown in Figure-7.

The results obtained using rSVD method are compared based on the PSNR, mean square error and running time with the projection matrix as plotted in Figure-8, Figure-9 and in Figure-10 respectively. Comparing to SVD, rSVD provides better result.

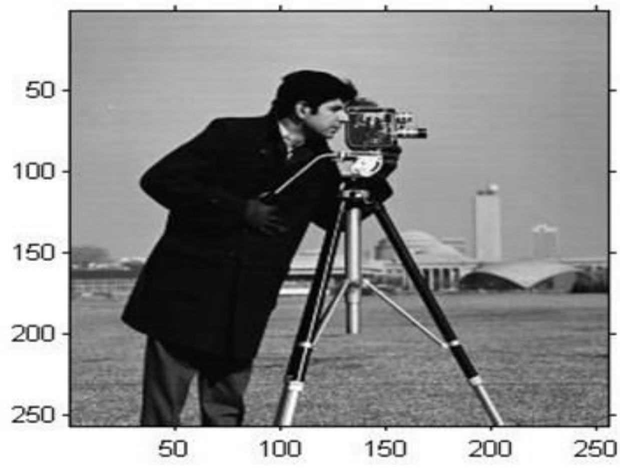

Figure-2. Original image.

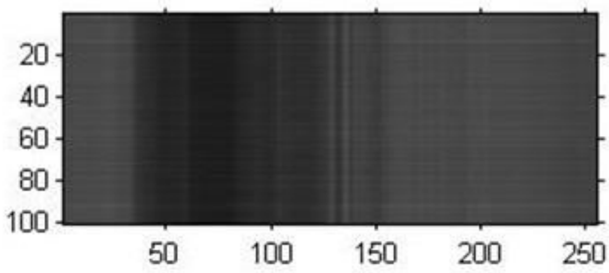

Figure-3. Projected along column.

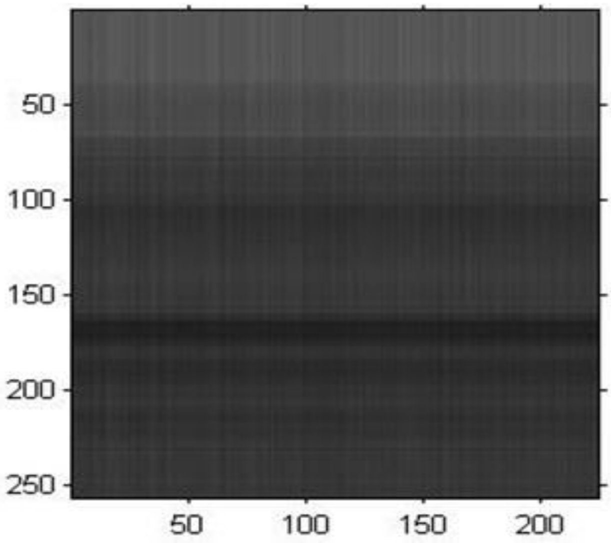

Figure-4. Projected along row.

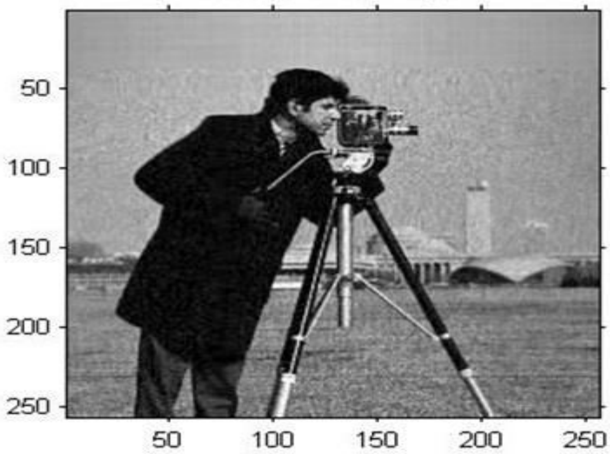

Figure-5. Reconstructed image using SVD.

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Figure-6. Reconstructed image using rSVD.

We have also considered the noise added to the image during transmission. The random noisy image as shown in Figure-11 is adaptively recovered using dictionary learning analysis. The reconstructed image after the removal of noise is shown in Figure-12. More accurate results are obtained and thus this novel method offers more applications in the image field.

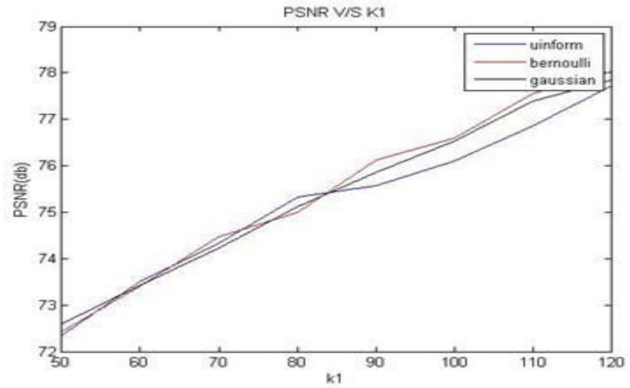

Figure-7. Different distributions with projection matrix.

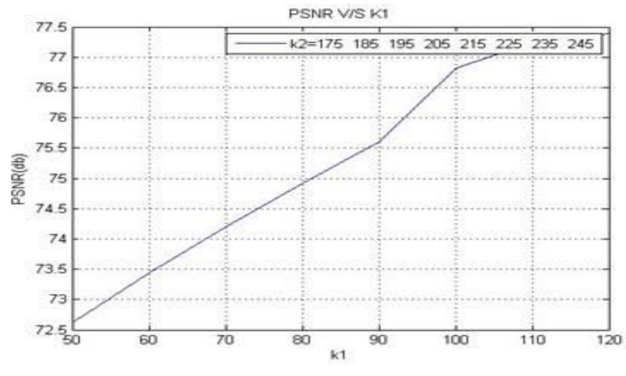

Figure-8. PSNR Curve obtained using rSVD.

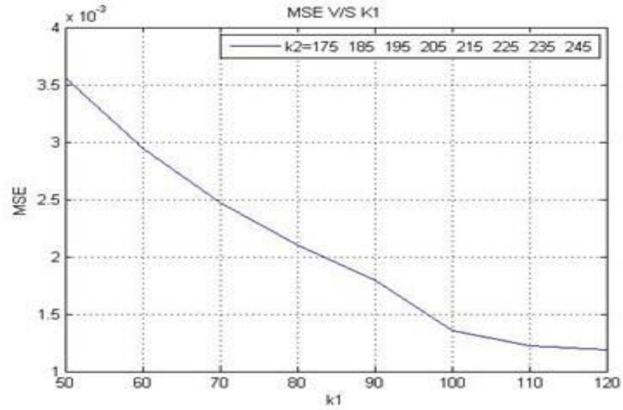

Figure-9. Mean square error curve obtained using rSVD.

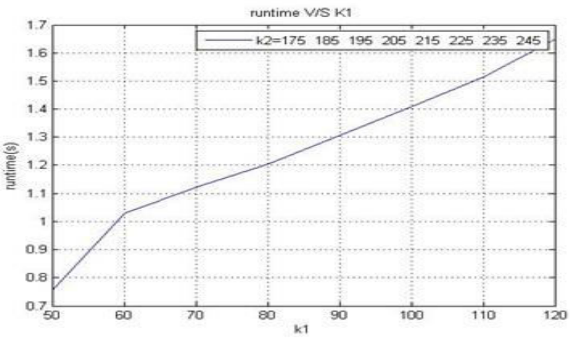

Figure-10. Run time curve obtained using rSVD.

Figure-11. Noisy image.

Figure-12. Reconstructed image using dictionary learning.

CONCLUSIONS

A novel method of adaptive removal of random noise from the randomly projected images is introduced. The projection of the images is done for the ease of transmission and processing using double random projection. The random noise generated during the transmission through the channel is removed adaptively based on the dictionary learning analysis. We have also reconstructed the original image with SVD and rSVD techniques and compared the performance of both. The results reveal that rSVD gives better result. Thus our work offers better reconstruction of image from the projected images which are corrupted with random noise.

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