International Journal of Advanced Research and Development
ISSN: 2455-4030, Impact Factor: RJIF 5.24
www.advancedjournal.com
Volume 2; Issue 1; January 2017; Page No. 01-04

Specialized hyper spectral image compression using 3 dimensional factorization technique and its thriving performance analysis

[1] S Hariharasudhan, [2] Dr. B Raghu

[1] Research Scholar, Bharath University, Tamil Nadu, India
[2] Principal, SVS Groups of Institutions, Warangal, Telangana, India

Abstract
Data compression is a fundamental and original requirement of digital information sequence of storage, broadcast and process of recovery. A digital image figures a momentous part in multi-media systems. This research work is highlighted on the expansion of a non-iterative with positive cum matrix factorization technique for image represented data compression. Though positive matrix factorization is a well-structured and recognized technique for image data compression, this technique is noteworthy on iterative method for factorization. In this research job, a very useful non-iterative technique for positive matrix factorization has been urbanized using Asymmetric Haar Discrete Wavelet transformation and experienced and tested with medical images. This 2-Dimensional matrix factorization system has also been stretched to 3D matrix factorization and useful for hyper-spectral image compression. Consequently a disparity signaling based BPSK (Bipolar Phase Shift Keying) system has been introduced for the transmission of factorized coefficients and tested for its performance in preservative White Gaussian Noise channel causing Rayleigh channels. A comprehensive statistical analysis has been prepared on the presentation of differential signaling related BPSK in communication channels exaggerated by Gaussian noise. The highly developed communication system has also been experienced using multi medical image data. The differential signaling related BPSK communication has a natural ability for partial discovery of errors without any transparency bits. With suitable and appropriate channel standard coding schemes at the value of overhead bits, the proposed system will be executed in improved manner.

Keywords: data compression, pixels, lossy compression, positive matrix factorization method (PMFM), bipolar phase shift keying

1. Introduction

The estimation of row factors and column factors is based on iterative calculations in this Positive Matrix Factorization Process (PMFP). In practice, the entire row factors and column factors are supposed to have a first value of 1. Then in a repeated order the column factors and row factors are added forward. At every step the outer products are computed, exactly compared with the generated PI values and the corresponding RMSE (Root Mean Square Error) is computed. This iterative process is repetitive until the RMSE reduces and converges to a smallest value which is considered to be of VLRMSE (Very Least Root Mean Square Error). For example, while considering a 4x4 matrix, a whole of 8 factors (4 column factors and 4 row factors) are to be approximated. During repeated iteration, the incremental change in any one factor will outcome in need for supplementary incremental changes in all the other related factors. Hence the dispensation time for iterations is huge. A computationally competent non-iterative of Positive Matrix Factorization Process, can be practically applied for image compression, which is been developed as a part of this complicated research effort. The Programme series transmission channel bandwidth and the corrective channel noise choose the capacity of the channel as enlightened by Shannon [1]. In digital communication, precise digitization is correlated to less significant quantization steps, ensuing in more number of bits created leading to amplified bit rate. Apparently this bit rate should be within the capability of the transmission channel. In multi-media applications, intrinsically the video image signals cause high bit rates. A distinctive (512X512) pixels image creates [512X512X8 (2097152)] bits per frame at 8 bits per pixel rate. A video image of 30 frames/sec creates [512X512X8X30] bits/sec (=63Mbps). The practice of images and videos above World Wide Web is always on the enlarged manner. As mentioned above, the visual multi media has to hold high bit rate. This requires high transitive bandwidth and leading storage space. Therefore, to transmit the data over band limited multi-channel, it is enviable to diminish the bit rate of the visual data using any appropriate compression system. Compression is the process of sinking the data bit rate. There are two methods of image compression – lossless compression and lossy compression. Lossless compression [2] reduces several redundancy and enables a trusty reproduction of the original or initial image from the image compressed data. In general, lossless compression achieves quite low compression ratio of about 3:1. Lossy compression [3] not only on dropping redundancy, but also on filtering the less essential details like the high frequency related content of an image. This results in higher compression ratios, classically 20:1 or greater, but with noticeable reduction in image quality. Many image compression algorithms [4], using different transformation techniques have been urbanized and are in utilization. Image compression algorithms related on iterative method of matrix factorization have also been mentioned [5]. Such iterative process demand augmented processing moment. It is enviable to minimize the processing period using a formula based non-iterative process for matrix factorization.

2. Non-iterative Process of Positive Matrix Factorization Method (PMFM)

Considering the case of a general 4x4 positive matrix I, it is to be factorized in to a 4x1 matrix (R) of row factors and a 1x4 matrix (C) of column factors. The outer products of R (r1, r2, r3, r4) and C (c1, c2, c3, c4) are predictable to ideally match the matrix I. However in practice the outer products yield the matrix $\hat{I}$.

$$I = \begin{pmatrix} I_{11} I_{12} I_{13} I_{14} \\ I_{21} I_{22} I_{23} I_{24} \\ I_{31} I_{32} I_{33} I_{34} \\ I_{41} I_{42} I_{43} I_{44} \end{pmatrix}$$

$$\hat{I} = \begin{pmatrix} R_1C_1\ R_1C_2\ R_1C_3 R_1C_4 \\ R_2C_1\ R_2C_2\ R_2C_3 R_2C_4 \\ R_3C_1\ R_3C_2\ R_3C_3 R_3C_4 \\ R_4C_1\ R_4C_2\ R_4C_3 R_4C_4 \end{pmatrix}$$

$$\hat{I} = \begin{pmatrix} \hat{I}_{11} \hat{I}_{12} \hat{I}_{13} \hat{I}_{14} \\ \hat{I}_{21} \hat{I}_{22} \hat{I}_{23} \hat{I}_{24} \\ \hat{I}_{31} \hat{I}_{32} \hat{I}_{33} \hat{I}_{34} \\ \hat{I}_{41} \hat{I}_{42} \hat{I}_{43} \hat{I}_{44} \end{pmatrix}$$

$$R = \begin{pmatrix} r1 \\ r2 \\ r3 \\ r4 \end{pmatrix}$$

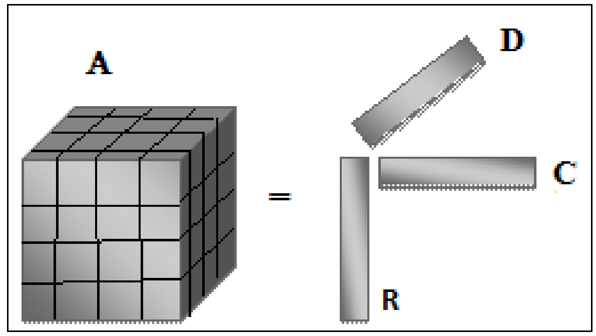
$$C = \begin{pmatrix} c1\ c2\ c3\ c4 \end{pmatrix}$$

The 3Dimensional process will be much useful for complicated compression of hyper-spectral images. The hyper spectral images involve a huge amount of storage space as the data density is high. Even a little amount of data compression will effect in a significant amount of saving in data storage.

Ordinary standard images are based on the amount of the pixel in the entire visible spectrum ranges from 400nm-700nm. Digital based images are good examples for such informative images. For applications like medical diagnostics multispectral images of the same object are used for accurate, effective and efficient analysis. These multi-spectral images are introduced by using multiple ready cameras all having a narrow band spectral-sensitivity. For example, a 3 band multi-spectral camera might have a lay down of cameras, each layer covering one band of visible and noticeable spectrum. The first camera might have a sensitivity in the band range of 400-500 nm, the second camera might be sensitive in the band range of 500-600nm and the third camera might be sensitive in the range of 600-700nm. If the number of bands are enlarged or increased, each covering a range of a 10nm in the visible spectrum of 400-700nm, then it would be introduced as a hyper spectral image. These hyper spectral images are useful in detailed and fine analysis of the sceneries or images. These hyper spectral images produce extremely dense data, requiring huge storage space. Compression of these images will effect in reduction of data storage prerequisite situations. This is mentioned with three dissimilar hyper spectral images [6], using 3D matrix factorization method. As a initial step, the growth of 3D matrix factorization method is explained as an addition of the 2D matrix factorization method.

3. Development of 3D matrix factorization method

A 4x4x4 cube matrix A with pixel intensity values I $_{111}$, $I_{1,2,1}$.....$I_{4,4,1}$, $I_{1,1,2}$, $I_{1,2,2}$ ......$I_{4,4,2}$, $I_{1,1,1}$, $I_{1,2,3}$ ....$I_{4,4,3}$, $I_{1,1,4}$, $I_{1,2,4}$, ...$I_{4,4,4}$ is shown in Figure 1 Mathematically, the 3D matrix can be factorized and represented by 3 orthogonal vectors R, C and D. Accordingly I1,1,1 = r1c1d1, ...$I_{4,4,4}$ = r4c4d4. In general I x,y,z = Rx * Cy * Dz.



Z1				Z3			
I_{111}	I_{121}	I_{131}	I_{141}	I_{113}	I_{123}	I_{133}	I_{143}
I_{211}	I_{221}	I_{231}	I_{241}	I_{213}	I_{223}	I_{233}	I_{243}
I_{311}	I_{321}	I_{331}	I_{341}	I_{313}	I_{323}	I_{333}	I_{343}
I_{411}	I_{421}	I_{431}	I_{441}	I_{413}	I_{423}	I_{433}	I_{443}
Z2				Z4			
I_{112}	I_{122}	I_{132}	I_{142}	I_{114}	I_{124}	I_{134}	I_{144}
I_{212}	I_{222}	I_{232}	I_{242}	I_{214}	I_{224}	I_{234}	I_{244}
I_{312}	I_{322}	I_{332}	I_{342}	I_{314}	I_{324}	I_{334}	I_{344}
I_{412}	I_{422}	I_{432}	I_{442}	I_{414}	I_{424}	I_{434}	I_{444}

Fig 1: Outer product representation of A

The technique of calculating the 4 column factors, 4 row factors and 4 depth factors of the cube matrix is passed out as an addition of the 2D matrix factorization method. As the initial step, the 3D (4x4x4) matrix is cut into pieces of 4 numbers of 2D (4x4) matrices (z1, z2, z3, z4). The column and row factors are expected using one of the four matrix acknowledged as the orientation matrix, as explained next. Let the summation of 16 pixel values of each of 4 matrices (z1, z2, z3, z4) be mentioned by Sz_1, Sz_2, Sz_3, Sz_4. The matrix having the greatest summation value is chosen as the refered matrix. If two or more matrix have the maximum summation, among one of them is preferred as the orientation matrix. For example, assume Sz2 is greatest and therefore z2 is the orientation matrix. The referred row factors are labeled as r1, r2, r3, r4 and the column factors are labeled as c1, c2, c3, and c4. These are the mandatory column and row factors for the cube matrix. Then the factors of depth d1, d2, d3, and d4 equivalent to z1, z2, z3, and z4 are projected. The depth factor d2 for the orientation matrix z2 is 1. Now the depth factor for other matrix, is calculated using the following formula of VLRMSE

Depth factor = Sum of the product of the consequent location PI values in Z1 & Z2/ Sum of the squares of the PI values of reference matrix Z2

Thus the depth factors d1, d2, d3, and d4 are calculated. The differences between the actual values I111 ……I444 and their corresponding reproduced product standards $\hat{I}_{111}$= r1c1d1, …… $\hat{I}_{444}$= r4c4d4 indicate the error, from which the LRMSE is estimated. Considering the convenience of transformation methods, single dimensional AH-DWT is functionally applied to all the 4 rows of all the matrices. The coefficients of the distorted matrices are subjected to 3Dimensional matrix factorization method.

4. Reconstruction of the hyper spectral images

The subsequent steps are utilized to recreate and renovate the hyper spectral image. Using the column factor C, row factor R, and depth factor D, the 64 DWT coefficients of the 4x4x4 cubes are estimated as the outer final products.

1. Applying inverse single dimensional DWT on the 64 DWT coefficients of recreated 4x4x4 cube, the 64 pixel intensity values of the 4x4x4 cube are estimated.
2. The similar practice is applied to all the cubes and therefore the original hyper spectral image is recreated. The above 3Dimensional matrix factorization method has been subjected to a number of hyper spectral images and the reproduction results are shown below

5. Reproduction of Outputs

The hyper spectral images of 3 dissimilar scenes [7] with column, row and band sizes of (1020x1339x32), (1021x1338x33)and(1017x1340x33) respectively, are revealed in Figure 2(a), Figure 3(a) and Figure 4 (a). The parallel compressed images using AH-DWT 3Dimensional matrix factorization are exposed in Figure 5(b), Figure 6(b) and Figure 7(b). For comparison the compression outputs using Tucker decomposition [8] are exposed in Figure 5(c), Figure 6(c) and Figure 7 (c). All the reproductions are carried out using MATLAB technology.

(a) (b) (c)

Fig 2

(a) (b) (c)

Fig 3

(a) (b) (c)

Fig 4

6. Performance Analysis of Compression Factor (CF), LRMSE and Total Processing Time (TPT), based on dice size

The mentioned image dealing is carried out using special dice sizes of (2x2x2), (4x4x4), (8x8x8) and (16x16x16). As the dice size increases the Least RMSE value increases and the Total Processing Time (TPT) also decreases. The results for outlooks are listed in Table 1

7. Performance analysis of scene 1 based on dice size

Table 1

Outlooks	AH-DWT related Matrix Factorization			AH-DWT related Tucker Decomposition		
	CF	LRMSE	TPT (sec)	CF	LRMSE	TPT (sec)
2x2x2	1.34	0.018	1068	1.325	0.0088	22434.12
4x4x4	4.3	0.0181	224.115	3.829	0.0147	8745.65
8x8x8	20.25	0.023	161.467	19.49	0.0254	1223.035
16x16x16	83.21	0.0548	148.67	80.512	0.038	321.11

8. Conclusion

From the above performance analysis it is obvious that the handing out time using non-iterative positive matrix factorization technique is a lesser amount compared to the Tucker decomposition Process.

9. References

1. Shannon CE. A Mathematical theory of communication, The Bell System Technical Journal. 1948; 27:379-423.
2. Weinberger MJ, Seroussi G, Sapiro G. LOCO-I: A low complexity, context-based, lossless image compression algorithm. IEEE conference on Data Compression (IEEE - DCC'96). 1996, 140-149.
3. Delp E, Mitchell O. Image compression using block truncation coding, IEEE Transactions on Communications. 1979; 27(9):1335-1342.
4. Antonini M, Barlaud M, Mathieu P, Daubechies I. Image coding using wavelet transform, IEEE Transactions on Image Processing, Vol.1, No.2, pp. 205-220, 1992.
5. Seung D, Lee L. Algorithms for non-negative matrix factorization, Advances in neural information processing systems. 2001; 13:556-562.
6. Foster DH, Amano K, Nascimento SMC, Foster M. j. Frequency of metamerism in natural scenes, Journal of the optical society of America- A. 2006; 23:2359-2372.
7. Theodore S. Rappaport, Wireless Communications. Principles and Practices, 2nd edition, Pearson publication. 2009, 210-214.
8. Karami A, Yazdi M, Mercier G. Compression of hyperspectral images using discerete wavelet transform and Tucker decomposition, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing. 2012; 5(2):444-450.