Image compression Using Daryaei Shuffle Singular Value Decomposition method

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Abstract— **Compressing data is a type of coding operation in which the input data are encoded in a way to occupy less space, to be recovered again in any desirable time, and to restore us the original data. Image Compression due to the increasing usage of information technology and some other reasons including storage capacity limit, etc. have been modeled as a key principle to design the distributed softwares. The Compression ratio and the rate of information recovery are the factors with which we can evaluate the methods of compression. In the current paper the technique of "daryaei SSVD" is presented which is designed based on "Shuffle Singular Value Decomposition & Singular Value Decomposition" which has more compression ratio.**

Keywords- image compression, singular value decomposition, Lempel-Ziv-Welch, DSSVD

I. INTRODUCTION (HEADING 1)

Digital images are mainly developed through sampling and quantization. The images occupy a large volume. Today's prevalent implementations such as databases, internet and the distributed systems need to reduce more volume of the data; the volume reduction process is very important [4].Nowadays, Many compression methods have been proposed to increase the resolution of all try to reduce the volume of data that are divided into two main groups:

A. Lossless technique [4], Thus, values of the main samples are precisely obtained again, found signal statistical excrements facilitate compression. The most important techniques are: Rle[4],Huffman coding[4], LZW coding [11], area coding.

B. technique with lossy[13] , thus, the main signal changes to some extent but more compression rates are obtained[6] the most important ones are: transformation coding [9], vector quantization[4], Fractal coding[4,5],block truncation coding[3,8], subband coding[10],svd[2],SSVD[1],jpeg[5,7] mpeg[13] and iSSVD.

This paper is defining an image compression lossy, the second section of the paper is on problem definition, the third section is proposing implementation solution, but the forth section is on experimental results, and finally, the fifth section is general conclusion.

problem definition

Main purpose of image compression is to eliminate more bits for image storage so that the compressed image is high quality with desirable resolution equal to the main image.[4] psnr is an effective criterion to measure quality of the renewed image.

$$PSNR = 10\log\frac{255^2}{MSE}(dB) \quad MSE = \sum\frac{D^2}{N}$$

D is the measured pixel difference with the main image; N is total number of the image pixels. Hence, it is to increase PSNR of the renewed images. Normal PSNR of the renewed images is between 30-40 decibel, also, compression rate is defined as below:

cr = (m × n)×8/ (codebit)

Cr is compression rate, and codebit is number of the compressed bits of the codes, and m×n is size of image in pixel. Every pixel is 8 bit, thus, the obtained result has been multiplied by 8.

Namely compression process is better; therefore, more compression quality coefficient result in lower rate of compression.

The paper is to define two lossless and lossy . main objective of the paper is to compress the image with appropriate resolution. Tested standard images maintain the quality resolution better in DSSVD rather than SSVD.

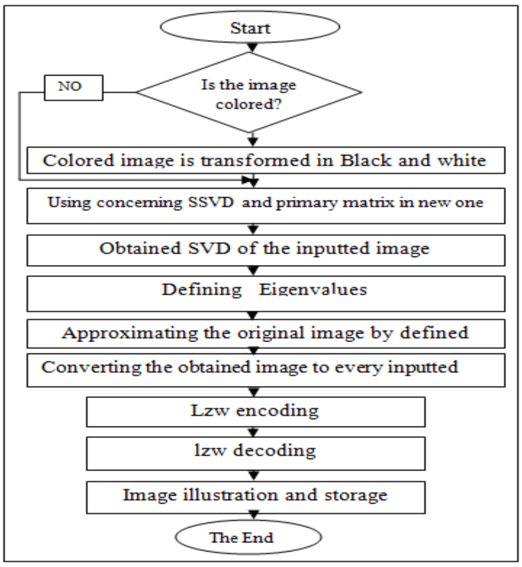
II. RECOMMENDED SOLUTIONS

A. DSSVD Method

In section 1, we discussed on compression methods lossy versus compression methods lossless, while even a bit is not lost , hence, the recommended solution for better image compression with more volume than that of SSVD is Lempel- Ziv-Welch

B. DSSVD flowchart.

Fig.1. DSSVD flowchart



C. Image Compression with DSSVD

The image is a matrix including some basic data identified and omitted by using matrix scale.

1. Approximation of A matrix with less elements of the main matrix

$: r < m \ , \ r < n$

$$A = \sigma_1 u_1 v_1^T + \sigma_2 u_2 v_2^T + \dots + \sigma_r u_r v_r^T + 0 u_{r+1} v_{r+1}^T + \dots$$

From A: 2. omitting zero eigenvalue

$$A = \sigma_1 u_1 v_1^T + \sigma_2 u_2 v_2^T + \dots + \sigma_r u_r v_r^T$$

Suppose that A is $N * N$ matrix and $N = n^2$, then $[X = S(A)]$ is so converted:[12]

a. Matrix a is broken down under $n * n$ ones..

b. Every sub-matrix is changed to a vector of the X matrix

c. Based on SVD vector it is concluded that:

3. $X\left[\lfloor i/n \rfloor n + \lfloor j/n \rfloor , (i \bmod n)n + j \bmod n\right] = A[i,j] \qquad X = S(A)$

d. Then with the method of Lempel-Ziv-Welch which is depended upon dictionary, every pixel of picture is compacted and in the dictionary instead of every pixel, the compacted strings are placed to the extent reaching a string existing in the dictionary. The last character of every string sent to the dictionary would be the first character of the next string, so it's added to the dictionary and this process repeats successively for the Coding Operation to accomplish dynamically. Afterwards, the operation of Lempel-Ziv-Welch is performed to display the image produced from DSSVD retaining image resolution, permanent PSNR, and more compression ratio.

III. EXPRIMENTAL RESULTS

All tested images are (m*m) square matrices that need (256*256*8)= 524288 byte storage memory, the occupied memory is to approximate main image with (2mk+k=30780) byte rank value. It is worth mentioning that k must be less than m^2/(1+2m)) , 127 for the images.

SSVD and DSSVD method are compared with rank 30 and 60:

Fig.2. Original Image

SSVD with rank=30

DSSVD with rank=30

SSVD with rank=60

DSSVD with rank=60

Compression rate of the above images and tested ones are so defined:

TABLE I. COMPRESSION RATIO

	compression ratio DSSVD vs SSVD	
	CR	*RANK*
compression ratio DSSVD vs SSVD	1.41	20
	1.42	30
	1.46	**60**
	1.32	100

TABLE II. MEMORY USAGE

compressed image memory usage than the original image				
RANK	DSSVD	ISSVD	SSVD	SVD
20	48.26	45.41 %	49.67 %	51.10 %
30	31.69	28.86 %	33.11 %	34.06 %
60	**15.09**	**12.32%**	**16.55 %**	**17.03 %**
100	8.61	5.71%	9.93%	10.22%

TABLE III. COMPARISON OF COMPRESSION METHODS

Compression rate	Resolution	Complexity	Coding		Compression method
			lossless	lossy	
✽	✽✽✽✽	✽	✓		Run length encoding
✽	✽✽✽✽	✽	✓		Huffman encoding
✽	✽✽✽✽	✽✽	✓		LZW encoding
✽	✽✽✽✽	✽✽✽	✓		Area coding
✽✽✽	✽	✽		✓	Transformation coding
✽✽	✽	✽✽		✓	Vector quantization
✽✽	✽✽	✽✽		✓	Fractal coding
✽✽	✽	✽✽		✓	Block truncation coding
✽✽	✽	✽		✓	Sub band coding
✽✽✽	✽✽	✽		✓	SVD
✽✽✽	✽✽✽	✽		✓	SSVD
✽✽✽	✽✽✽	✽✽		✓	JPEG
✽✽✽	✽✽✽	✽✽		✓	MPEG
✽✽✽✽	✽✽✽	✽		✓	ISSVD
✽✽✽✽	✽✽✽	✽✽		✓	DSSVD

Main objective of DSSVD image compression with less eigen value is to reduce used memory for better resolution, thus, in average, table.2 with 60 eigen value saves 1.5% of the memory through DSSVD compared with SSVD while 82.9%, 83.4%,87.68% and 84.91% of the memory are saved by SVD,SSVD,ISSVD and DSSVD systems respectively. Accordingly, we approximated the image very well through algorithm for the non-standard.

IV. CONCLUSION

DSSVD produces an indistinguishable image to the main one with lower eigen value, with only 15% volume of the main image. Even, DSSVD has not lost a bit of obtained data through SSVD, thus the compression rate is increased 1.5% with the maintained resolution. Also, DSSVD algorithm could not be implemented for colored images, because it limits output image, consequently, inputted colored image is outputted white and black.

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