# A Wavelet Transform Algorithm for $2^n$Shades Image

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*Abstract*--**Wavelet anatomization is globally appreciated up to the sixtieth part of an hour tools for time-frequency. It acquires an exceptional development based on Fourier fractionation and plays a consequential character in the signal processing remarkably in image compression. By analyzing the relations of the coefficients between every main block and the complete image, we can locate the catalogue location of the sub-band of each son block in the same sub-band of the whole image is same as that of the son block in the origin image. Many image compression algorithms (lossy or lossless) have already been devised adhering to their perspective point of view. In this paper we propose conceptually an algorithm for image compression for minimizing a number of bits for storing an image into disk and reducing spatial redundancy and correlation between pixels.**

***Keywords**: spatial redundancy, SPIHT, sharp edge, Wavelet.*

## I. INTRODUCTION

The conception of a transform is habitual to mathematicians. The hypothesis is to metamorphose mathematical extent (a number, a vector, a function, or anything else) to another form, where it may inspect non friendly but may exhibit useful characteristics. After transforming a quantity into another form, we can use this to solve the problem and to perform a calculation. Now we can understand a transformation [8] using following example.

**(*XCVI)*** X ***(XII)*** **→ 96 X 12 = 1152 → MCLII**

Here we want to solve multiplication of two Romans ancient so first we convert into modern (Arabic) number then multiply transformed modern number, afterward convert number into roman primeval.

Now before going detailed survey on image compression here we can distinguish many images on behalf of its pixel intensity value.

A Monochromatic image (bi level image) [4] [9] [10], this type of image is straightforward category of image because its pixel can have one of two value black and white and represented by one bit only.

A Gray scale image, Gray scale image can have $2^n$ no. of gray shades. Its pixel can have one of 0 to n-1 value [5] [10]. Each pixel of this type of image is represented by bytes. The group most significant bits of its pixel are most significant bit plane. Due to this it has n bit planes.

A Continuous tone image, in a continuous tone image, when a surrounding district pixel (adjacent pixel) is not similar by just one unit of bits then it seems to be difficult for human eyes to distinguish. Basically this type of image have many identical color or represented by one area of colors and RGB [5] color pattern. Example of continuous tone image (natural image) is, taking a photograph through digital camera, scanning a photograph or painting.

A synthetic image (discrete tone image or graphical image), basically discrete tone image is non natural image [5] (artificial image) but every artificial image is not discrete tone image e.g. Computer generated image look like a continuous image spite of being artificially generated. In this type of image adjacent pixel are similar (identical) or vary significantly and also does not have noise or blurring. An Image compression algorithm (lossy algorithm) which applied for continuous tone image often does not handle the sharp edge for example compressing text data. Consequence of this, different compression methods to be apply for this type of image to removing the redundancy or spatial correlation [4] [9] .example of synthetic image, photograph of artificial object or machine, text etc.

There are many image compression algorithms which one applied for different type of images. Basically it's intuitively understandable that each image may have characteristics of redundancy [11] but they are redundant in different manner.

Functions [12] utilized in science and engineering often use time as their parameter. We therefore say that a function g(t) is symbolized in the time domain [7]. Since an orthodox function oscillates, we can imagine of it as being identical to a wave, and we may make an effort to represent it as a wave (or as a combination of waves). When this is finalized, we represent the resulting function [10] [12] by G(f), where f stands for the frequency of the wave, and we can say that the function is represented in the frequency domain. This turns out to be a useful concept, since many operations on functions are easy to carry out in the frequency domain [13]. Transforming a function between the time and frequency domains [8] is easy when the function is periodic, but it can also be done for certain non periodic functions [12].

The objective of image compression is to eschew or minimize the number of bits to represent any image while maintaining the visual perception of an image(statue). Basically main goal is to exploit the spatial redundancy [10] and to minimize the correlation [9] [10] between pixels. Wavelets [14] became popular in few past years in mathematics and digital signal processing area because of their ability to effectively represent and analyze data. Typical application of wavelets in digital signal processing is image compression.

Wavelet analysis is globally appreciated up to the sixtieth part of an hour tools for time-frequency [1] [13]. It gets an unprecedented development based on Fourier analysis and plays an important role in the signal processing especially in image compression. By analyzing the relations of the coefficients between each son block and the whole image, we can find the index position of the sub-band [7] [8] of each son block in the same sub-band of the whole image is same as that of the son block in the origin image**.**

In recent years, most of the research activities in image coding have shifted from DCT to wavelet transforms, especially after Shapiro introduced his famous embedded zero tree wavelet coder (EZW) [7] [15]. The SPIHT (Set Partition in Hierarchical Tree) [1] [15] algorithm is unique in that it does not directly transmit the contents of the sets, the pixel values, or the pixel coordinates. What it does transmit is the decisions made in each step of the progression of the trees that define the structure of the image. Because only decisions are being transmitted, the pixel value is defined by what points the decisions are made and their outcomes, while the coordinates of the pixels are defined by which tree and what part of that tree the decision is being made on. The advantage to this is that the decoder can have an identical algorithm to be able to identify with each of the decisions and create identical sets along with the encoder. We use metamorphosed SPIHT algorithm for image compression and discuss the results in this paper.

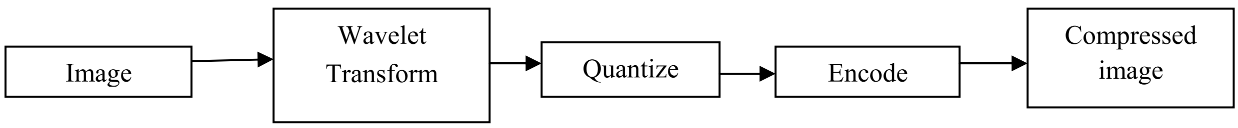



Figure 1 Compression of an image

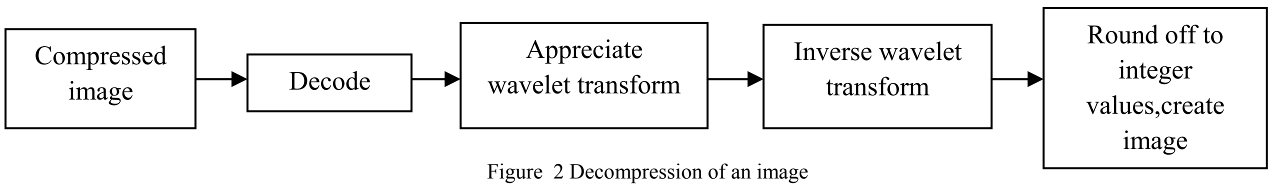



Figure 2 Decompression of an image

After this introduction we have given related work in section 2, proposed compression algorithm in section 3, performance analysis in section 4 and finally the conclusion in last section 5.

## II. RELATED WORK

There are only two methods for image compression, first one is lossy compression and another one is lossless compression. In the lossy compression distortion between original image and reconstructed image is tends to big while in the lossless compression distortion ration between both image is 1.

In this literature, we shall concentrate on lossy compression techniques like the EZW [7] algorithm, the WDR algorithm [8], and the ASWDR [8] [16] algorithm. These are recently new technique for image compression, which have lowest error per compression and highest perceptual quality yet reported. Before going detailed survey on this type of algorithm, we shall list one another compression algorithms that are available.

Before we examine the algorithms listed above, we shall outline the basic steps that are common to all wavelet-based image compression algorithms.

The five stages of compression and decompression are shown in Figs. 1 and 2. All of the steps shown in the compression diagram are invertible, hence lossless, except for the Quantize step. Quantizing [4] refers to a reduction of the precision of the floating point [] values of the wavelet transform [5], which are typically either 32-bit or 64-bit floating point numbers. To use less bits in the compressed transform which is necessary if compression of 8 bpp or 12 bpp images is to be achieved. These transform values must be expressed with less bits for each value. This leads to rounding error. These approximate, quantized, wavelet transforms will produce approximations to the images when an inverse transform is performed.

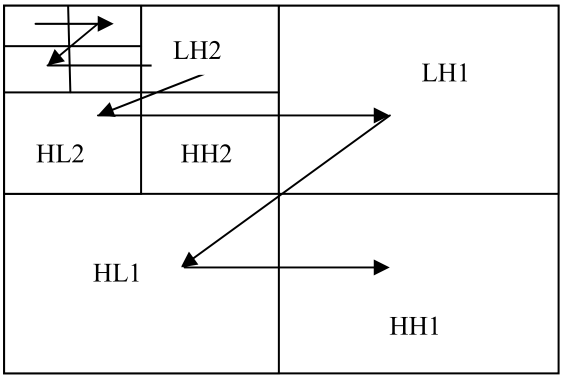



Figure 3

Let us now turn to these improved wavelet image compression algorithms. The algorithms to be discussed are the EZW [15] algorithm and WDR [19] algorithm.

The EZW algorithm [7] [15] was one of the first algorithms to show the full power of wavelet-based image compression [5]. Many other algorithms build upon the fundamental concepts that were first introduced with EZW. The EZW method, as implemented in practice, starts by performing the 9-tap symmetric quadrature mirror filter (QMF) wavelet transform [14] . The main loop is then repeated for each values of the threshold that are halved at the end of iteration. The threshold is used to calculate a significance map of significant and insignificant wavelet coefficients. Zero trees are used to represent the significance map in an efficient way. The main steps are as follows:

1. Initialization: Set the threshold T to the smallest power of 2 that is greater than $(\max_{i,j}) |c_{i,j}|/2$, where $c_{i,j}$ are the wavelet coefficients.

2. Significance map coding: Scan all the coefficients in a predefined way and output a symbol when $|c_{i,j}| > T$. When the decoder inputs this symbol, it sets $c_{i,j} = \pm 1.5T$.

3. Refinement: Refine each significant coefficient by sending one more bit of its binary representation. When the decoder receives this, it increments the current coefficient value by ±0.25T.

4. Set T = T/2, and go to step 2 if more iterations are needed.

A wavelet coefficient $c_{i,j}$ is considered insignificant with respect to the current threshold T if $|c_{i,j}| \leq T$. The zero tree data structure is based on the following well known experimental result: If a wavelet coefficient at a coarse scale (i.e., high in the image pyramid) is insignificant with respect to a given threshold T, then all of the coefficients of the same orientation in the same spatial location at finer scales (i.e., located lower in the pyramid) are very likely to be insignificant with respect to T. In the each iteration, all the coefficients are scanned in the order shown in Figure 3.This guarantees that when a node is visited; all its parents will already have been scanned. The scan starts at the lowest frequency sub band $LL_n$, continues with subbands$HL_n$,$LH_n$ and $HH_n$,, and drops to level n-1, where it scans $HL_{n-1}$, $LH_{n-1}$,, and $HH_{n-1}$,. Each subband is fully scanned before the algorithm proceeds to the next subband.Each coefficient visited in t he scan is classified as a zerotree root (ZTR), an isolated zero (IZ), positive significant (POS), or negative significant (NEG). A zerotree root is a coefficient that is insignificant and all its descendants (in the same spatial orientation tree) are also insignificant. Such a coefficient becomes the root of a zero tree [15] [19] [20]. It is encoded with a special symbol (denoted by ZTR), and the important point is that its descendants don’t have to be encoded in the current iteration. When the decoder inputs a ZTR symbol, it assigns a zero value to the coefficients and to all its descendants in the spatial orientation tree. Their values get improved (refined) in subsequent iterations. An isolated zero is a coefficient that is insignificant but has some significant descendants. Such a coefficient is encoded with the special IZ symbol. The other two classes are coefficients that are significant and are positive or negative. The flowchart of

Figure 4 illustrates this classification. Notice that a coefficient is classified into one of five classes, but the fifth class (a zero tree node) is not encoded.

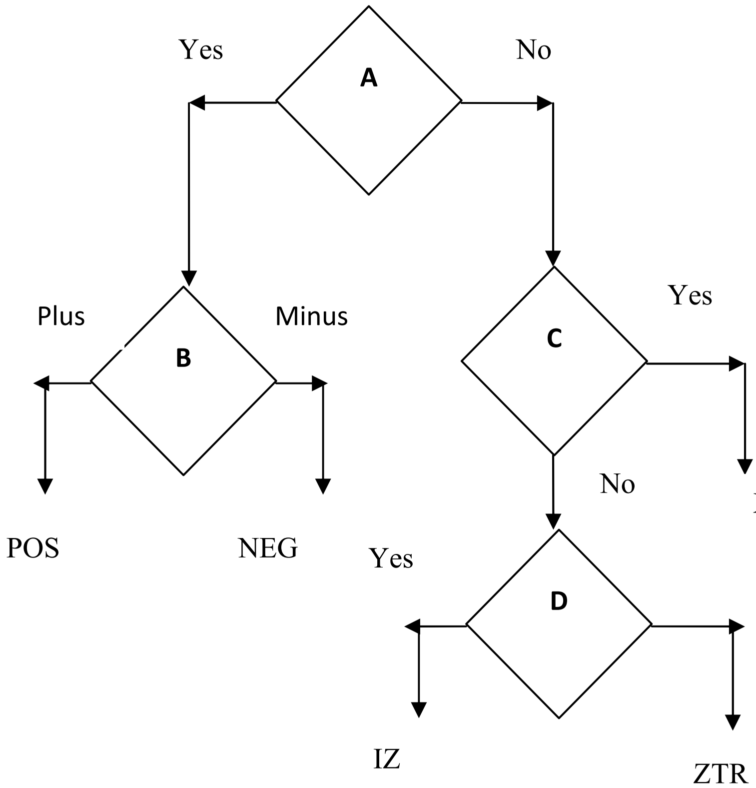
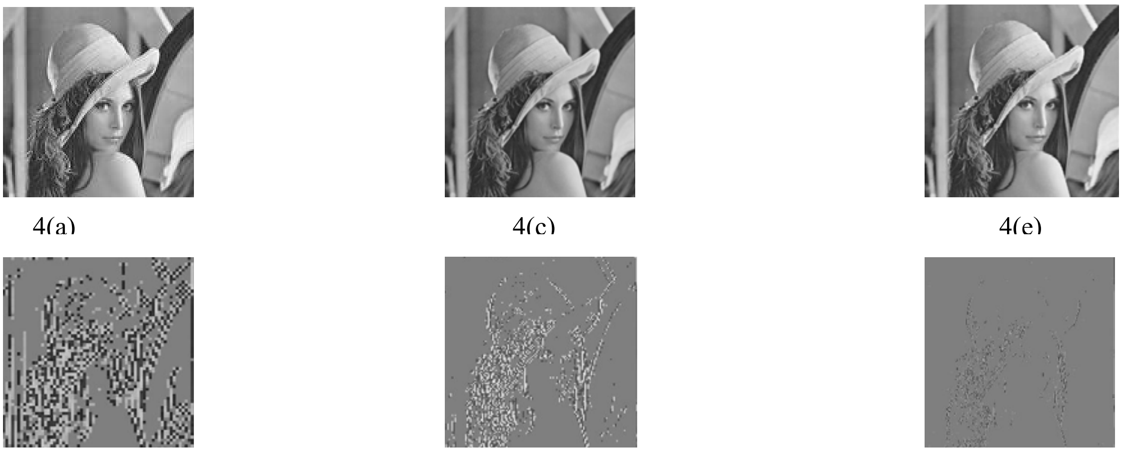



Figure 4

A=is coefficient significant, B=sign, C=coefficient does descend from a zero tree root, D=coefficient does descendants have significant, X=insignificant do not code

Zerotrees [8] can only be useful if they occur frequently. Fortunately, with wavelet transforms of natural scenes, the multi resolution structure of the wavelet transform does produce many zero trees. For example, consider the images shown in Fig. 4. In Fig. 4(a) we show the 2nd all-low pass sub band of a Daub 9/7 transform of the Lena image. The image 4(b) on its right is the 3rd vertical subband produced from this all-lowpass subband, with a threshold of 16. Notice that there are large patches of grey pixels in this image. These represent insignificant transform values for the threshold of 16. These insignificant values correspond to regions of nearly constant, or nearly linearly graded, intensities in the image in 4(a).Such intensities are nearly orthogonal to the analyzing Daub 9/7 wavelets. Zerotrees arise for the threshold of 16 because in image 4(c).the 2nd all lowpass subband. There are similar regions of constant or linearly graded intensities. In fact, it was precisely these regions which were smoothed and down sampled to create the corresponding regions in image 4(a). These regions in image 4(c) produce insignificant values in the same relative locations (The child locations) in the 2nd vertical subband shown in image 4(d).



4(a) 4(c) 4(e)

4(b) 4(d) 4(f)

Figure 5

(a) 2nd all-lowpass subband. (b) 3rd vertical subband. (c) 1st all lowpass subband. (d) 2nd vertical subband. (e) Original Lena. (f) 1st vertical subband.

Likewise, there are uniformly grey regions in the same relative locations in the 1st vertical subband [see Fig. 4(f)]. Because the 2nd vertical subband in Fig. 4(d) is magnified by a factor of two in each dimension, and the 3rd vertical subband in 4(b) is magnified by a factor of four in each dimension, it follows that the common regions of grey background shown in these three vertical subbands are all zero trees. Similar images could be shown for horizontal and diagonal subbands, and they would also indicate a large number of zerotrees.

WDR Algorithm, One of the defects of SPIHT is that it only implicitly locates the position of significant coefficients. This makes it difficult to perform operations, such as region selection on compressed data, which depend on the exact position of significant transform values. By region selection, also known as region of interest (ROI), we mean selecting a portion of a compressed image which requires increased resolution. This can occur, for example, with a portion of a low resolution medical image that has been sent at a low bpp rate in order to arrive quickly.

Such compressed data operations are possible with the Wavelet Difference Reduction (WDR) algorithm of Tian andWells. The term difference reduction refers to the way in which WDR encodes the locations of significant wavelet transform values, which we shall describe below. Although WDR will not typically produce higher PSNR values than SPIHT, we shall see that WDR can produce perceptually superior images, especially at high compression ratios.

The only difference between WDR and the Bit-plane encoding described above is in the significance pass. In WDR, the output from the significance pass consists of the signs of significant values along with sequences of bits which concisely describe the precise locations of significant values.

Suppose that the significant values are w(2) = +34.2, w(3) = -33:5, w(7) = +48:2, w(12) = +40:34, and w(34) = -54:36. The indices for these

Significant values are 2, 3, 7, 12, and 34. Rather than working with these values, WDR works with their successive differences: 2, 1, 4, 5, and 22. In this latter list, the first number is the starting index and each successive number is the number of steps needed to reach the next index. The binary expansions of these successive differences are 10, 1, 100, 101, and 10110. Since the most significant bit for each of these expansions is always 1, this bit can be dropped and the signs of the significant transform values can be used instead as separators in the symbol stream. The resulting symbol stream for this example is then +0 - +00 + 01 - 0110.

In next section we propose an algorithm for minimizing the constraints of above deal in algorithms.

## III. PROPOSED COMPRESSION ALGORITHM

The main objective is to compress the image with efficiently and after all applying reversed process (decompression algorithm) to get original image which have nearest PSNR ratio with that image.

In this algorithm, basically we will use block truncating coding over SPIHT algorithm. Basically we used the combination of both above algorithms and get better result. The principle used by the block truncation coding (BTC) method and its variants is to quantize pixels in an image while preserving the first two or three statistical moments. In the basic BTC method, the image is divided into blocks (normally 4×4 or 8×8 pixels each).

**STEP FIRST**

**Compression _Algorithm (M)**

1. An image is divided into nxn block (usually 2x2, 4x4, and 8x8).
2. Assuming that a block is containing n pixel with intensity value $p_1$ to $p_n$.
3. Calculate the mean and variance of each block

$$\text{Mean } p=\frac{1}{n}\sum_{i=0}^{n} p_i,\ \text{Variance\_}p^2 = \frac{1}{n}\sum_{i=0}^{n} p_i^2,\ \text{Deviation } \alpha=\sqrt{\text{mean} - \text{varinace}}$$

4. Applying Mentphorsed SPIHT algorithm to each block.
5. Calculate three values for each block $p_{max}$, $p_{min}$ and $p_{base}$.
   If ($p_{max} \geq p_{base}$) then $p_i$=$p_{max}$
   Otherwise $p_i$=$p_{min}$
6. It is intuitively clear that $n^+$ pixels are greater than base value and $n^-$ pixel less than its base value ($p_{base}$).
7. Now update the 4 pixel intensity value using following formula.

$$p_{max}=p_{max}+ \alpha\sqrt{\frac{n^+}{n^-}},p_{min}=p_{min}+ \alpha\sqrt{\frac{n^+}{n^-}}$$

**STEP SECOND**

**Mentphorsed SPIHT algorithm**

**Step 1** (Initialize). Choose initial threshold, T =$T_0$, such that all transform values satisfy |w (m)| < $T_0$ and at least one transform value satisfies |w (m) |≥$T_0/2$ . Set the initial scan order to be the baseline scan order.
**Step 2** (Update threshold). Let $T_k$ =$T_{k-1}/2$.
**Step 3** (Significance pass). Perform the following procedure on the insignificant indices in the scan order:
Initialize step-counter C = 0
    Let Cold = 0
        Do
        Get next insignificant index m
        Increment step-counter C by 1
        If |w (m) |≥$T_k$ then
        Output sign w (m) and
            Set $w_Q$(m) = $T_k$
        Move m to end of sequence of significant indices
        Let n = C - $C_{old}$
        Set $C_{old}$ = C
        If n > 1 then
    Output reduced binary expansion of n
    Else if |w(m)| < = $T_k$ then
    Let $w_Q$(m) retain its initial value of 0
**Step 4** (Refinement pass). Scan through significant values found with higher threshold values $T_j$ , for j < k (if k = 1 skip this step). For each significant value w (m), do the following:

If |w (m)| € [$w_Q$(m), $w_Q$(m)+ $T_k$),
then Output bit 0
Else if |w (m)| € [$w_Q$(m) + $T_k$, $w_Q$(m) + 2$T_k$),
Then Output bit 1
Replace value of [$w_Q$(m) by $w_Q$(m) + $T_k$.

**Step 5** (Create new scan order). For each level j in the wavelet transform (except for j = 1), scan through the significant values using the old scan order. The initial part of the new scan order at level j □ 1 consists of the indices for insignificant values corresponding to the child indices of these level j significant values. Then, scan again through the insignificant values at level j using the old scan order. Append to the initial part of the new scan order at level j-1 the indices for insignificant values corresponding to the child indices of these level j significant values. Note: No change is made to the scan order at level L, where L is the number of levels in the wavelet transform.

**Step 6 (**Loop). Repeat steps 2 through 5.

## IV. PERFORMANECE ANAYSIS

The above discussed algorithm has been implemented in MATLAB-7.0.In this image compression algorithm we take Lena image, firstly we compressed with existing SPIHT algorithm and after all compressed with proposed algorithm then following outcome are coming.

Original image

SPIHT, 0.0625 bpp

MSPIHT, 0.0625 bpp

Original image

SPIHT, 0.125 bpp

MSPIHT, 0.125 bpp

Although modified SPIHT is simple, competitive with SPIHT in PSNR values, and often provides better perceptual results, there is still room for improvement.

In Table 1 we show the numbers of significant values encoded by SPIHT and MSPIHT for four different images. In almost every case, MSPIHT was able to encode more values than SPIHT. This gives an a posteriori validation of the predictive scheme employed by MSPIHT

As quantitative support for the superiority of ASWDR in preserving edge details, we show in Table 1 the values for three different edge correlations$Y_k$, k = 3, 4, and 5. Here k denotes how many levels in the Daub 9/7 wavelet transform were used. A higher value of k means that edge detail at lower resolutions was considered in computing the edge correlation. These edge correlations show that MSPIHT is superior over several resolution levels in preserving edges in the airfield image at the low bit rate of 0:0625 bpp.

Table 1

| Image/Method | SPHIT | MSPIHT | %increase |
|---|---|---|---|
| Lena,0.125bpp | 5241 | 5458 | 4.1% |
| Lena,0.25 bpp | 10450 | 11105 | 6.3% |
| Lena, 0.5 bpp | 20809 | 22370 | 7.5% |
| Goldhill,0.125bpp | 57809 | 5634 | -1.9% |
| Goldhill, 0.25 bpp | 10210 | 10210 | -1.9% |
| Goldhill, 0.5 bpp | 23394 | 23394 | 2.1% |
| Barbara,0.125bpp | 5571 | 5571 | 4.2% |
| Barbara, 0.25 bpp | 11681 | 12174 | 4.2% |
| Barbara, 0.5 bpp | 23697 | 24915 | 5.1% |
| Aireld, 0.125 bpp | 5388 | 5736 | 6.5% |
| Aireld, 0.25 bpp | 10519 | 11228 | 6.7% |
| Aireld, 0.5 bpp | 19950 | 21814 | 9.3% |

Table 2

| Corr./Method | SPIHT | WDR | MSPIHT |
|---|---|---|---|
| $Y_1$ | .665 | :692 | :711 |
| $Y_2$ | .780 | :817 | :827 |
| $Y_3$ | :845 | 879 | 885 |

## V. CONCLUSION

This paper presents an improved compression algorithm for gray scale image to reduce the correlation and spatial redundancy between pixels of an image. Our proposed algorithm is useful to maintain the compression ratio and quality of an image. This algorithm was test on different gray scale images with different sizes. Our future works is update or extend this proposed algorithm for color images.

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