ISSN: 0976-9102(ONLINE)
DOI: 10.21917/ijivp.2011.0033


# PARAMETRIC EVALUATION ON THE PERFORMANCE OF VARIOUS IMAGE COMPRESSION ALGORITHMS

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***Abstract***
***Wavelet analysis plays a vital role in the signal processing especially in image compression. In this paper, various compression algorithms like block truncation coding, EZW and SPIHT are studied and analyzed; its algorithm idea and steps are given. The parameters for all these algorithms are analyzed and the best parameter for each of these compression algorithms is found out***

***Keywords:***
***Block Truncation Coding, Embedded Zero Wavelet, SPIHT***

## 1. INTRODUCTION

Today people interact with digital images in one form or the other. Large storage capacity is needed for storing the images and a wide bandwidth is needed to transmit the images across the net. This leads to the development of compression algorithms. The main goal of image compression is to minimize the size in bytes of a graphics file without degrading the quality of the image [1]. The reduction in file size allows more images to be stored in a given amount of disk or memory space. It also reduces the time required for images to be sent over the Internet or downloaded from Web pages. Nowadays, the wavelet transforms are widely used for image compression as they efficiently decorrelate the information held in natural images by splitting the signal into high-pass and low-pass subbands [2]. Wavelets play a major role in image processing applications, because of its flexibility in representing images and its ability to take into account Human Visual System characteristic. It is used in areas like signal processing, fractal analysis [3], numerical analysis [4], statistics [5], and astronomy [6] and in fingerprints [7]. Compression algorithms on wavelets have been developed [8]-[10] over the years to perform image compression which give high compression ratios compared to other algorithms. These algorithms have been investigated by many researchers [11, 12]. Wavelets are used in applications, such as image compression, de-noising, human vision, radar etc.

Today researchers have made a study on the higher order metrics for SPIHT based image compression [21], made evaluation on wavelet filters for image compression and discussed the important features of wavelet functions and filters used in sub band coding to convert image into wavelet coefficients [17]. An improved SPIHT algorithm was proposed to increase the efficiency [18]. Colour Image Compression Based on the Embedded Zerotree Wavelet [19] was developed for colour images, based on the omission and restoration of wavelet subbands. In recent years hybrid schemes using SPIHT has been used for effective compression [16, 20, 22, and 23].

Image compression scheme can be broadly classified into two types. (i) lossless compression scheme (ii) lossy compression scheme. Lossless compression scheme is preferred in the case of multimedia applications. Lossy compression is also acceptable in fast transmission of still images over the Internet. Popular image compression techniques like DCT based transform coding[13] and vector quantization [14,15] are lossy block based techniques. Lossless compression scheme is preferred in the case of multimedia applications. In lossless compression scheme, the reconstructed image exactly resembles the original image without any loss of information. That is it can be reconstructed exactly without any change in the intensity values. But the compression ratio that can be achieved using a lossless compression scheme is usually less. Lossy encoding for images is obtained using transform encoding methods which remove the redundancies by mapping the pixels into a transform domain prior to encoding. Applications like Satellite Image processing and certain medical imaging do not tolerate any data loss and are compressed using lossless methods.

This paper is organized as follows: Section 1 is the introduction outlining the background and purpose of this study. In section 2 Preliminary concepts of the work is discussed. Section 3 deals with error metrics. Experimental results are presented in Section 4. Finally the conclusion of the research is given in Section 5.

## 2. PRELIMINARY CONCEPTS OF THE WORK

### 2.1 THE SPIHT ALGORITHM

Set Partitioning in Hierarchical Trees in an efficient image compression algorithm. It is developed by Said and Pearlman in 1996 [8]. It is based on zero tree coding of EZW. It uses three lists of co-efficients.

1. List of Significant Pixels(LSP)
2. List of Insignificant Pixels (LIP)
3. List of Insignificant Sets(LIS)

The wavelet co-efficients and trees are grouped into sets based on their significance information. The co-efficients at the top of the pyramid have a strong spatial relationship with their children. The algorithm searches for significant pixels throughout the pyramid tree. The co-efficients are ordered according to a significance test and this information is stored in the three lists.

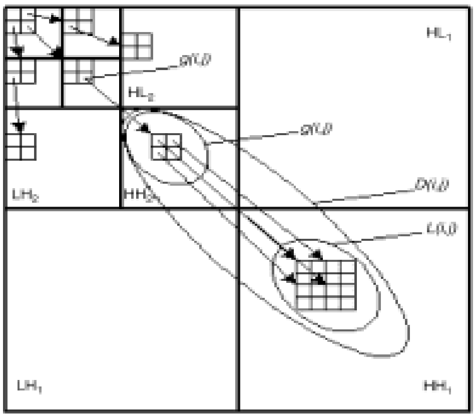


Fig.1. Offspring dependencies in the pyramid structure

A wavelet co-efficient at location (i,j) in the pyramid representation has four offsprings at locations: O(i,j)={(2i,2j),(2i,2j+1),(2i+1,2j),(2i+1,2j+1)}. This pyramid structure is called spatial orientation tree.

The encoding consists of two main stages.

- Sorting
- Refinement

SPIHT considers two different types of trees.

- Type A – All the descendants are not significant.
- Type B- All descendants except the children are not significant

***2.1.1 Algorithm:***

1. Initialization:
   - Set LSP as empty list
   - Add all the co-efficients without any parents to LIP
   - Add all co-efficients with descendants to LIS as type A.
2. Sorting:

   For each entry (i,j) of the LIP
   - Output Sn(i,j) . the function Sn(i,j) is o if all the descendants of (i,j) are below the threshold and 1 otherwise
   - If Sn(i,j) is 1, move (i,j) to the LSP and output the sign of wavelet co efficient Ci,j.

   For each entry (i,j) in LIS do and if the entry is of type A then
   - Output Sn(D(i,j).
   - If Sn(D(i,j)) is 1 then for each (k,l) ∈ O(i,j) do
   - Output Sn(k,l)
   - If Sn(k,l) is 1 then add (k,l) to the LSP and output the sign of Ck,l else add (k,l) to the end of LIS as entry of type B and go to step II;else remove entry (i,j) from the LIS.

   If the entry is of type B then
   - Output Sn(L(i,j))
   - If it is 1 then add each (k,l) ∈ε O(i,j) to the end of LIS as entry of type A.
   - Remove (i,j) from LIS.
3. Refinement Pass: For all entries (i,j) in the LSP except those included in the last sorting pass, output the nth most significant bit of Ci,j.
4. Decrement n and go to step 2.

   O(i,j)- set of co ordinates of the off spring(i,j).

   D(i,j)- Set of co ordinates of all descendants (i,j).

   H(i,j) – Set of all tree roots in the highest level of the pyramid.

   L(i,j)=D(i,j)-O(i,j)

## 2.2 BLOCK TRUNCATION CODING

It is a lossy image compression technique for grayscale images. It was first proposed by Mitchell and Delp at Purdue University.

***2.2.1 Algorithm:***

1. The given image of size m*m is divided into blocks of size n*n.
2. For each block, the mean and standard deviation are calculated.
3. A two level quantization on the block is performed as follows:
4. $y(i,j) \begin{cases} = 1, x(i,j) > \bar{x} \\ = 0, x(i,j) \leq \bar{x} \end{cases}$

   where, x(i,j) are pixel elements of original block and y(i,j) are elements of the compressed block.
5. The n*n bit block is transmitted along with the values of Mean and Standard Deviation.
6. Reconstruction is made using two values a and b.

   $a = \bar{x} - \sigma\sqrt{q/m - q}$

   $b = \bar{x} + \sigma\sqrt{}q/m - q$

   where σ is the standard deviation

   m- total number of pixels in the block

   q- number of pixels greater than the mean $(\bar{x})$
7. To reconstruct the image, elements assigned a 0 are replaced with the value “a” and elements assigned a 1 are replaced with the “b” value.

   $X(i,j) = \begin{cases} a, y(i,j) = 0 \\ b, y(i,j) = 1 \end{cases}$

## 2.3 EMBEDDED ZEROTREE WAVELET

It is a remarkable image compression algorithm by Shapiro [9] which generates the bits in the bitstream in order of importance giving a fully embedded code. The dependencies between the wavelet co efficients of different sub bands are exploited to create zero trees. A zero tree is composed of a parent and its descendants which is shown in the Fig.2.

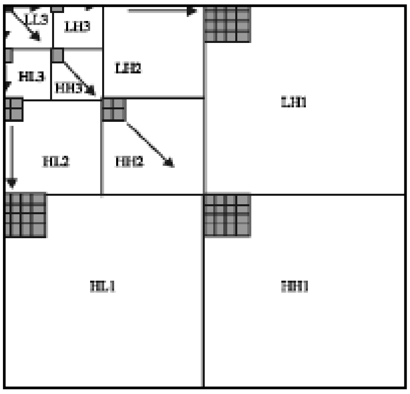

Fig.2. Parent-descendant dependencies between sub bands

### *2.3.1 Algorithm:*

1. Initialization:
   Apply wavelet transform to the image and determine the threshold T0 which is given by
   $T0 = 2 \log 2 (|Cmax|)$
   where, Cmax is the largest wavelet coefficients.
2. Significance Test:
   The wavelet co-efficients are scanned in the order shown in the Fig.2 and a symbol is returned for every co efficient.
3. Subordinate Pass:
   The significance test is always followed by a subordinate pass where the coded data get coded in 1 or 0 to be transmitted. The process for subordinate pass is illustrated below;

```
subord_threshold=current_threshold/2;
for all elements on subordinate list do
 {
     if coefficient>subord_threshold then
    {
       output a one;
      coefficient = coefficient- subord_threshold;
    }
     else output a zero;
   }
```

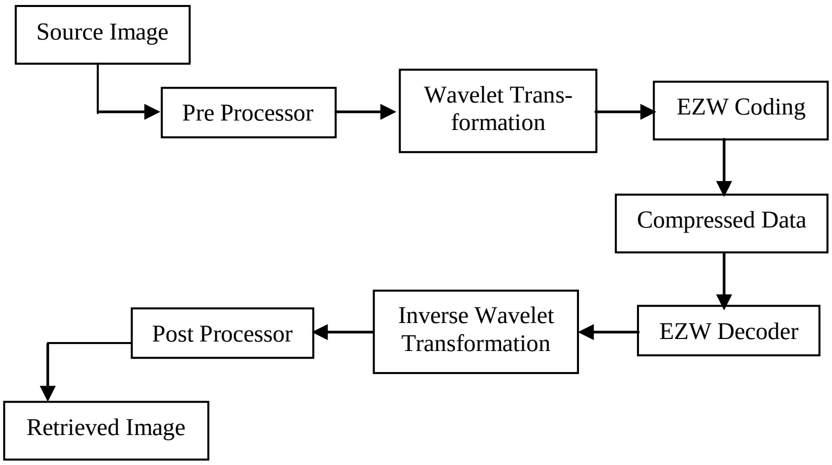


Fig.3. EZW coding system

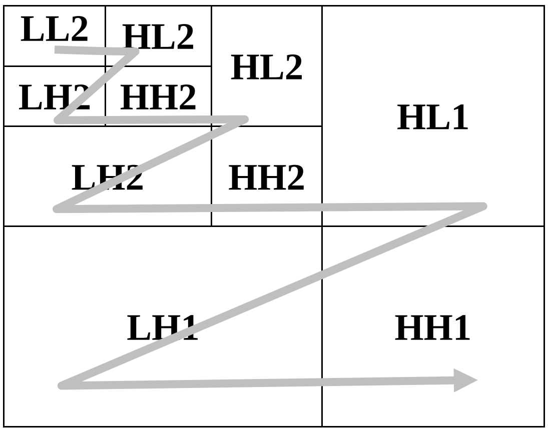


Fig.4(a). Scanning a zero tree

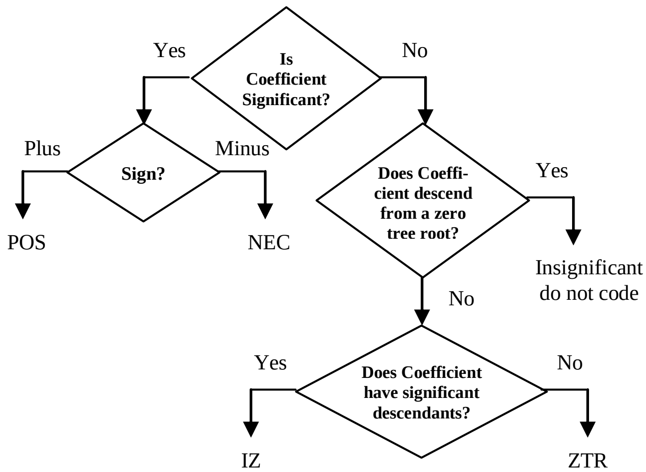


Fig.4(b). Classifying a co- efficient

## 3. METRICS

It is used for assessing the quality of the image. It helps to rank the different compression methods so that the best compression algorithm for a specific application can be identified. The following error metrics are used for comparing the image compression techniques:

1. Mean Square Error (MSE)

$$MSE = \frac{1}{MN}\sum_{y=1}^{M}\sum_{x=1}^{N}\left[I(x,y) - I'(x,y)\right]$$

2. Peak Signal to Noise Ratio (PSNR)

$$\text{PSNR}=20^{*} \log_{10}\left(\frac{255}{\sqrt{MSE}}\right)$$

where, I(x, y) – Original Image

I'(x, y) – Reconstructed Image

A higher value of PSNR is good because the ratio of signal to noise is higher. Signal is the original image and noise is the reconstructed image.

## 4. EXPERIMENTAL RESULTS

### 4.1 SPIHT ALGORITHM

SPIHT algorithm has been tested with Lena image of size 256 * 256. It is found that as level of decomposition increases, PSNR value also increases. For a decomposition level of 8, 'coif2' filter yields high PSNR value of 35.63db and filter 'dmey' gives a PSNR value of 35.61db. PSNR value of filter 'haar' is lesser compared to all other filters.

SPIHT algorithm has been tested for various images like Lena, Cameraman and Elaine and the compression and decompression times are noted. As the levels of decomposition increases, both the compression and decompression time increases. High PSNR value is got for cameraman image. It is found that compared to EZW algorithm the time taken to compress and decompress the image is very less in SPIHT algorithm.

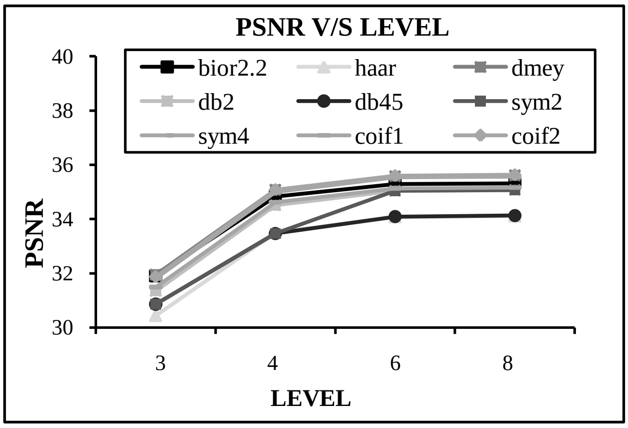


Fig.5. Analysis chart for SPIHT based Image Compression System

Table.1. Analysis of SPIHT based Image Compression System

| LEVEL | bior2.2 | haar | dmey | db2 | db45 | sym2 | sym4 | coif1 | coif2 |
|---|---|---|---|---|---|---|---|---|---|
| 3 | 31.91 | 30.44 | 31.95 | 31.35 | 30.86 | 30.86 | 31.81 | 31.49 | 31.87 |
| 4 | 34.83 | 33.5 | 35.08 | 34.51 | 33.47 | 33.47 | 35 | 34.62 | 35.08 |
| 6 | 35.29 | 34.08 | 35.58 | 35.04 | 34.09 | 35.04 | 35.54 | 35.13 | 35.6 |
| 8 | 35.32 | 34.11 | 35.61 | 35.07 | 34.13 | 35.07 | 35.56 | 35.16 | 35.63 |

Table.2. Analysis of SPIHT algorithm for filter 'db45'

| Image | Level of decomposition | Compression time | Decompression Time | PSNR (db) |
|---|---|---|---|---|
| Lena | 3 | 4.5938 | 2.0156 | 30.86 |
| | 5 | 6.5938 | 4.9063 | 33.97 |
| | 6 | 6.9844 | 4.4375 | 34.09 |
| Cameraman | 3 | 4.8906 | 1.3594 | 37.90 |
| | 5 | 4.5156 | 2.0781 | 44.07 |
| | 6 | 4.7188 | 2.2344 | 44.25 |
| Elaine | 3 | 4.1406 | 1.1094 | 31.48 |
| | 5 | 5.0469 | 2.8125 | 35.30 |
| | 6 | 5.0781 | 2.8906 | 35.37 |

Table.3. Analysis of BTC based Image Compression System

| Block Size | PSNR |
|---|---|
| 2*2 | 35.48 |
| 4*4 | 30.41 |
| 8*8 | 27.33 |
| 16*16 | 25.11 |

## 4.2 BLOCK TRUNCATION CODING

BTC algorithm has been tested with Lena image of size 256 * 256.From table.2, we find that as the block size increases, PSNR value decreases. PSNR value of 35.48db is got for a block size 2*2. and PSNR value of 25.10db is got for a block size 16 * 16.

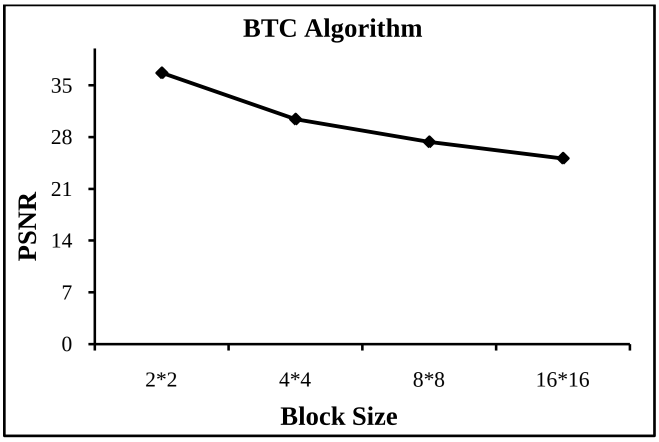


Fig.6. Analysis chart for BTC based Image Compression System

## 4.3 EZW ALGORITHM

Lena image of size 256 * 256 has been used for testing the EZW algorithm and the results are tabulated

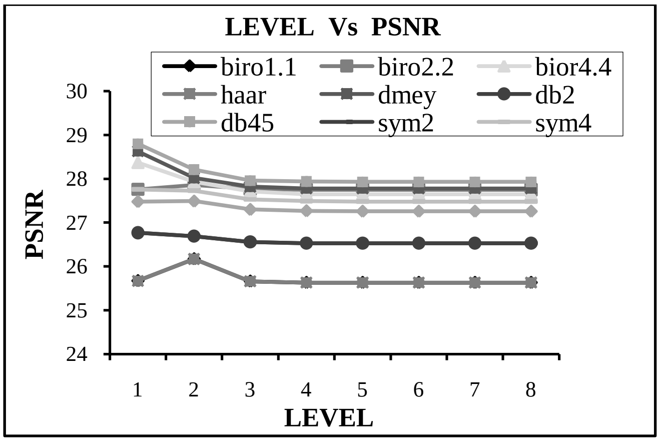


Fig.7. Analysis chart for EZW based Image Compression System

It is found that as levels of decomposition increases there is no change in PSNR value. It remains the same after Level 4. For a decomposition level of 1, filter 'db45' yields a high PSNR of 28.8db when compared with other filters. Filters 'dmey' and 'biro4.4' has PSNR value above 28db for single level of decomposition. Filters biro2.2, sym2 and coif2 rank next having a PSNR value above 27db. Haar filter has the poor performance when compared to other filters having a PSNR value of 25.67db.The compression and decompression times for various images like Lena, Cameraman and Elaine are found using EZW algorithm for filter 'db45'.

Table.4. Analysis of EZW based Image Compression System

| Level | biro1.1 | biro2.2 | bior4.4 | haar | dmey | db2 | db45 | sym2 | sym4 | coif2 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 25.67 | 27.76 | 28.37 | 25.7 | 28.6 | 26.8 | 28.8 | 26.77 | 27.76 | 27.48 |
| 2 | 26.17 | 27.86 | 27.93 | 26.2 | 28 | 26.7 | 28.2 | 26.69 | 27.73 | 27.49 |
| 3 | 25.66 | 27.77 | 27.71 | 25.7 | 27.8 | 26.6 | 28 | 26.56 | 27.53 | 27.30 |
| 4 | 25.63 | 27.75 | 27.65 | 25.6 | 27.8 | 26.5 | 27.9 | 26.53 | 27.49 | 27.27 |
| 5 | 25.63 | 27.75 | 27.65 | 25.6 | 27.8 | 26.5 | 27.9 | 26.53 | 27.48 | 27.26 |
| 6 | 25.63 | 27.75 | 27.65 | 25.6 | 27.8 | 26.5 | 27.9 | 26.53 | 27.48 | 27.26 |
| 7 | 25.63 | 27.75 | 27.65 | 25.6 | 27.8 | 26.5 | 27.9 | 26.53 | 27.48 | 27.26 |
| 8 | 25.63 | 27.75 | 27.65 | 25.6 | 27.8 | 26.5 | 27.9 | 26.53 | 27.48 | 27.26 |

Table.5. Analysis of EZW algorithm for filter 'db45'

| Image | Levels of decomposition | Compression time | Decompression Time | PSNR (db) |
|---|---|---|---|---|
| Lena | 3 | 81.7813 | 163.1875 | 27.96 |
| | 5 | 81.9688 | 151.8438 | 27.93 |
| | 6 | 78.75 | 150.25 | 27.93 |
| Cameraman | 3 | 59.8906 | 123.3906 | 33.48 |
| | 5 | 56.1250 | 113.2188 | 33.38 |
| | 6 | 55.7031 | 112.5313 | 33.38 |
| Elaine | 3 | 64.5156 | 126.2188 | 30.15 |
| | 5 | 60.3750 | 116.6406 | 30.11 |
| | 6 | 59.2031 | 115.9844 | 30.11 |

As the levels of decomposition increases, both the compression and decompression time decreases and PSNR value remains constant. High PSNR value is got for cameraman image. It is found that compared to SPIHT algorithm the time taken to compress and decompress the image is more in EZW algorithm.

## 5. CONCLUSION

By analyzing the various tables and graphs, it is observed that the SPIHT algorithm is able to achieve good performance with less computational effort. It is the best coding technique for all general types of images. For the same level of decomposition and for the same filter ‘coif2’ SPIHT yields a PSNR value of 35.63db while EZW yields a value of 27.26db.

Table.6. Analysis of the three algorithms

| Algorithms | PSNR |
|---|---|
| SPIHT | 35.63 |
| BTC | 35.48 |
| EZW | 27.26 |

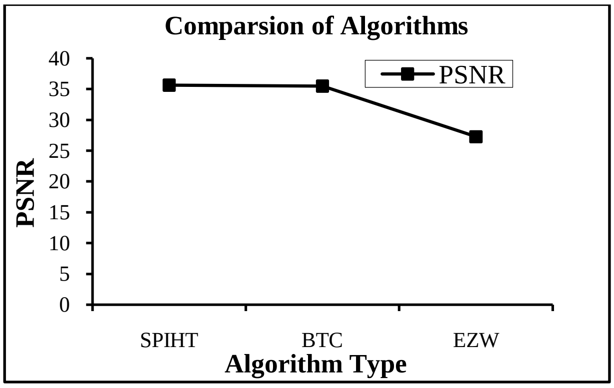


Fig.8. Comparison of Algorithms

BTC ranks next to SPIHT by yielding a PSNR value of 35.48db for a block size of 2*2. While comparing these three algorithms SPIHT yields better PSNR values. Thus SPIHT compression algorithm performs better at higher level of decomposition. The original image and the reconstructed image using SPIHT, EZW and BTC compression algorithms for various images are shown in Fig. 9 and it is seen that SPIHT gives better PSNR values compared to the other two algorithms.

| Original Image | SPIHT | EZW | BTC |
|---|---|---|---|
|  |  |  |  |
| Elaine | PSNR=35.37 | PSNR=30.11 | PSNR=32.2049 |
|  |  |  |  |
| Lena | PSNR=38.97 | PSNR=27.96 | PSNR=30.4081 |
|  |  |  |  |
| Cameraman | PSNR=44.25 | PSNR=33.38 | PSNR=31.7638 |

Fig.9. Results obtained from experimentation with 3 test images

## ACKNOWLEDGEMENT

Authors would like to thank the reviewers of the paper and also special thanks to my research guide for providing her valuable guidance for the completion of the work.

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