HYBRID IMAGE COMPRESSION BY BLURRING BACKGROUND AND NON-EDGES

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ABSTRACT

Two hybrid image compression methods are proposed in this paper. In these methods the vital part of the image is completely restorable and non vital part of the image may restorable with insignificant loss. The two methods proposed are 1.Hybrid Image Compression with Background Blurring (HICBB) 2. Hybrid Image Compression with Non-Edges Blurring (HICNB). In HICBB, the image is first segmented into two segments namely Background and Foreground. Then the background of the image is blurred using image smoothing algorithm. Finally the blurred background and unchanged foreground are combined and compressed using standard lossless compression method. In HICNB, the image is first subjected to edge detection to find the edges and non-edges. Then the non-edges are blurred using the smoothing algorithm. Finally the blurred non-edges and unchanged edges are combined and compressed using standard lossless compression methods.

KEYWORDS

Edge Detection, Smoothing, Image Compression, Dilation

1. INTRODUCTION

Even though the memory capacities of computers have increased as new technologies are emerging, the requirement for more storage space is also increasing as more data are needed to be stored. In the case of image data, the spatial and color resolutions are increased for the betterment of image quality, thus requires more space to store images. Image compression is one of the solutions to meet the storage requirements. In image compression, there are two major classifications; they are lossless and lossy compression. In lossless image compression, the entire data can be restored after decompression, but not in the case of lossy compression. Vector quantization (VQ) [11],[14] , wavelet transformation [1],[3],[8], [13],[17],[21] techniques are widely used in addition to various other methods[18] in image compression. The problem in lossless compression is that, the compression ratio is very less; where as in the lossy compression the compression ratio is very high but may loose vital information of the image. Some of the related works carried out in hybrid image compression [5], [21] incorporated different compression schemes like predictive vector quantization (PVQ) and discrete cosine transform domain VQ (DCTVQ) in a single image compression. But the proposed method differs from these techniques by combining both lossy and lossless pixels in the image.

The proposed method performs a hybrid compression, which makes a balance on compression ratio and image quality by preserving the vital information. In this approach two different methods are specified depend on the vitality of the image data. The foreground image is very important than the background image, similarly edges are playing a very important role in image visualization, thus edges becomes very important in images. Considering the importance of image components, and the effect of smoothness in image compression, the first method segments the image as foreground and background, then the background of the image is subjected to smoothing and the foreground is kept unaffected. Finally the resultant image is compressed with lossless compression method. The second method detects the edges and non-edge area, blur the non-edge area and the edges are kept unaffected, and then the resultant image is compressed with lossless compression method. There are enormous amount of work on image compression is carried out both in lossless [1] [15] [20] and lossy [5] [7] [11] [13] [16] [17] compression. Very few works are carried out for Hybrid Image compression [5], [21].

In the proposed work, for image compression, the edge detection, segmentation, smoothing and dilation techniques are used. For edge detection, segmentation [9], smoothing and dilation, there are lots of work has been carried out [19]. A simple and a time efficient method to detect edges and segmentation used in the proposed work are described in section 3, detailed description of the proposed method is given in section 4, the results and discussion are given in section 5 and the concluding remarks are given in section 6.

2. RELATED WORK

An edge preserving image compression model base on subband coding and iterative constrained least square regularization is presented in [5] by S.W Hong and P.Bao. In this the edge is preserved by using standard edge pattern vectors. The edge information is subjected to vector quantization based on the edge patterns and is stored using run length encoding (RLE). Zhe-Ming Lu, Hui Pei presented a method in [21] that uses different compression schemes like predictive vector quantization (PVQ) and discrete cosine transform domain VQ (DCTVQ) in a single image compression . According to Charles F. Hall in [22] high contrast edge information can be isolated in the upper bit plane (the most significant bit) of most types of imagery. Simple run length encoding of this bit plane can be used to preserve the location and approximate peak amplitude of the edge information. Xiao-Yan presented an encoding scheme in [23] which is the combination of fractal image encoding and wavelet decomposition. In [24] the coder determines whether a local fractal term will improve each image block by examining its rate/distortion contribution, so that only beneficial fractal terms are used. Secondly, the decoder deduces the offset parameters for the local fractal transform from the basis functions alone, by inferring the dominant edge position, so that no offset information is required.

3. EDGE DETECTION, SEGMENTATION AND BLURRING

Let X be a matrix of order m x n, represents the image of width m and height n. The domain for Xi,j is [0,255] , for any i=1..m, any j=1..n. G be a matrix of the same order as of X for holding the gradient value, with a domain [0,255]. E be a binary matrix of the same order as of X and holding the status of the pixel if it is in edge or not, having the domain [0,1].

3.1. Edge Detection

The edge detection is performed by finding the maximum gradient value of a pixel from its three neighboring pixels as shown in Figure 1. If the maximum value of the gradients satisfies some precondition then the corresponding pixel is considered to be in edge. The computation to detect whether a pixel $X_{i,j}$ at (i,j) is in edge or not is given in (1) and (2)

$X_{i,j}$	$X_{i+1,j}$
$X_{i,j+1}$	$X_{i+1,j+1}$

Figure 1- Neighboring Pixels.

$$G_{i,j}=\max\{|X_{i,j}-X_{i+1,j}|,|X_{i,j}-X_{i+1,j+1}|,|X_{i,j}-X_{i,j+1}|\} \quad (1)$$

$$E_{ij}=\begin{cases}1 & \text{if } G_{ij}>Th\\ 0 & \text{otherwise}\end{cases} \quad (2)$$

where Th is a predefined threshold value. Here a threshold value is selected empirically, and the precondition to a pixel $X_{i,j}$ at (i,j) to be in edge is that the value of Gi,j should be greater than the threshold, otherwise the pixel is said to be in non-edge area.

3.2. Segmentation

The segmentation of foreground and background image is computed after detecting the edges. The scan line algorithm is used to fill in the area surrounded by the edges. The horizontal and vertical scanning is performed independently and the result is combined to get the foreground filled image. In horizontal scan line process, the scanning starts from left to right to find non-zero element in the matrix E. For scanning line or row j, the column i varies from 1 towards n, and checks for non-zero value in Ei,j , once non zero Ei,j is found, set starting column 'is' as i, now the scan proceeds from right to left to find the right most edge pixel, the column starts from n towards 1 to find a non-zero element at row j once nonzero Eij is found ,set ending column 'ie' as i. Now fill the line Eis,j to Eie,j. After repeating the process for all the rows in the image, the horizontally filled image will be ready, similarly vertical scan line process starts from top to bottom that is keeping the column fixed and change the row from 1 to m. After completing vertical scan line process, the two images are combined by logical AND operation. The resultant image is a binary image where the foreground is represented by 1 and the background is represented by 0. The segmented image is used in the proposed algorithm HICBB to decide whether to blur a pixel or not.

3.3. Blurring

To blur the image, smoothing is performed in the image by convolving a smoothing filter on the image. In this case, a smoothing filter of width w is set up and convolved with the input image. The smoothing filter (SF) is a matrix of order w x w with all the elements of value $1/w^2$. The convolution operation at any location (ij) in the input image X can be written as follows

$$\sum_{l=-w/2}^{w/2} \sum_{k=-w/2}^{w/2} X_{i+k,\, j+l} * \mathrm{SF}_{k,1}$$

The result image obtained by the convolution operation is the blurred image.

4. PROPOSED HYBRID IMAGE COMPRESSION METHODS

4.1. Hybrid Image Compression with Background Blurring (HICBB)

The HICBB method compresses the image with insignificant loss in background of the image and with no loss in the foreground of the image. To achieve this, HICBB first segments the input image (α) into foreground and background image as described in section 3. The segmented image (β) is a binary image as described in section 3.2. Then a blurred image (χ) of the original input image is created. The χ is created according to the blurring procedure described in section 3.3. After this a hybrid image (δ) is formed by composing the χ and α .To compose the χ and α, the β is used as a reference. The δ is composed to have the pixel values of α at locations where the values of β are 1 and the remaining locations are having the pixel values of χ at the corresponding locations. This can be written as follows

$$\delta_{\mathrm{ij}} = \begin{cases} \alpha_{\mathrm{ij}} \text{ if } \beta_{\mathrm{ij}} \text{ is } 1 \\ \chi_{\mathrm{ij}} \text{ otherwise} \end{cases} \qquad (3)$$

Finally the composed δ is compressed using standard lossless compression method (used JPEG2000) to get the Compressed Image (ς). The compression ratio is expected to be comparatively better than lossless image compression and the image quality is to be better than lossy compression. More details are discussed in section 5. The block diagram in figure 2 gives the overall architecture of this method. The entire operation in HICBB can be written in few simple steps as follows

HICBB Algorithm:

Step 1 : Read the input image α

Step 2 : Find the segments foreground and background β

Step 3 : α is blurred to get the χ

Step 4 : Find the δ by composing α and χ as per (3) according to β.

Step 5 : Compress the δ with no loss to get ς.

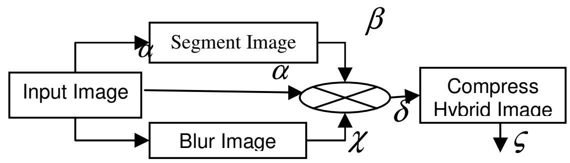


Figure – 2 Block Diagram of HICBB

4.2. Hybrid Image Compression with Non-Edge Blurring (HICNB)

The HICNB method compresses the image edges with no loss and with insignificant loss on non-edge areas in the image. To perform this hybrid compression, the edges (ε) in the input image α are detected first by using the method described in the earlier section 3. Then a smoothed image χ of the original input image α is created. The χ, is created according to the smoothing procedure described in section 3.3. Now, the hybrid image δ can be composed from α, χ and ε.

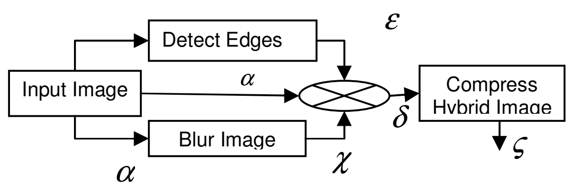


Figure – 3 Block Diagram of HICNB

The δ is composed to have the pixel values of α at locations where the values of ε are 1 and the remaining locations are having the pixel values of χ at the corresponding locations. This can be written as follows

$$\delta_{ij} = \begin{cases} \alpha_{\mathrm{ij}} & \text{if } \varepsilon_{ij} \text{ is } 1 \\ \chi_{\mathrm{ij}} & \text{otherwise} \end{cases} \qquad (4)$$

The hybrid image δ is finally compressed using standard lossless compression method (used JPEG2000).In this method also the compression ratio is expected to be comparatively better than lossless image compression and the image quality is to be better than lossy compression. The block diagram shown in figure 3 gives the overall idea of this method. The entire process of HICNB can be written in few simple steps as follows

HICNB Algorithm:

Step 1 : Read the input image α

Step 2 : Find the Edges ε

Step 3 : α is blurred to get χ

Step 4 : Find the δ by composing α and χ as per (4) according to ε.

Step 5 : Compress the δ with no loss to get ς.

5. RESULTS AND DISCUSSION

The results obtained from the implementation of the proposed algorithms are shown in figures from 4 to 9 and in tables I and II. The HICBB and HICNB method are implemented according to the description in section 3 and tested with a set of twelve images shown in figure 6. The implemented smoothing window size is 9. The compressed images by HICBB and HICNB are shown in figure 4.b and figure 4.d. An important problem of distortion along the edges can be observed in some of the decompressed images. This problem is due to the fact of blurring. The problem can be easily seen by zooming up the image, the figures from 5.a to 5.d shows eight times enlarged rectangular portion of the images shown in figures from 4.a to 4.f respectively.

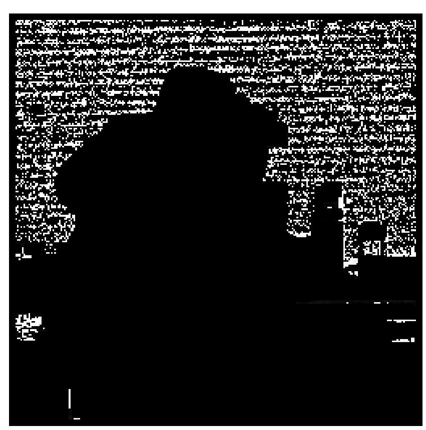
a)Original Image

b)Compressed Background Blurred Image

c)Compressed Dilated Background Blurred Image

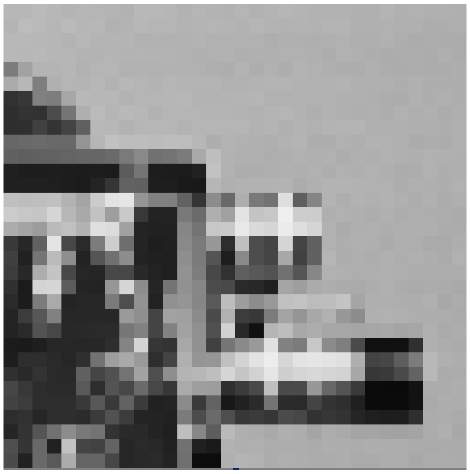
d)Compressed Non Edge Blurred Image

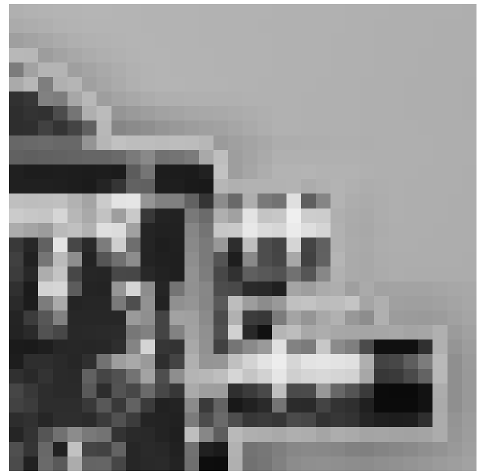
e)Compressed Dilated – Non Edge Blurred Image

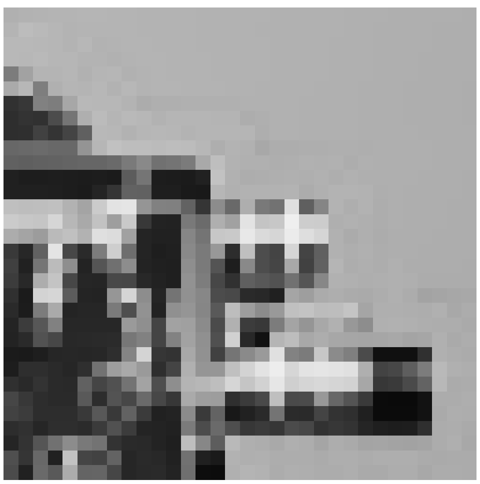


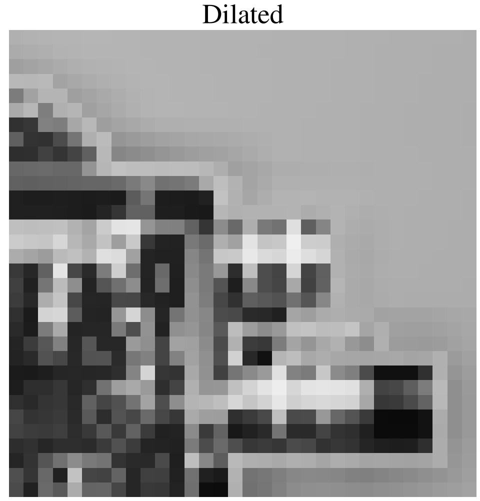
f)Blurred | Input Image(a) - Dilated Background Blurred Image(c)|

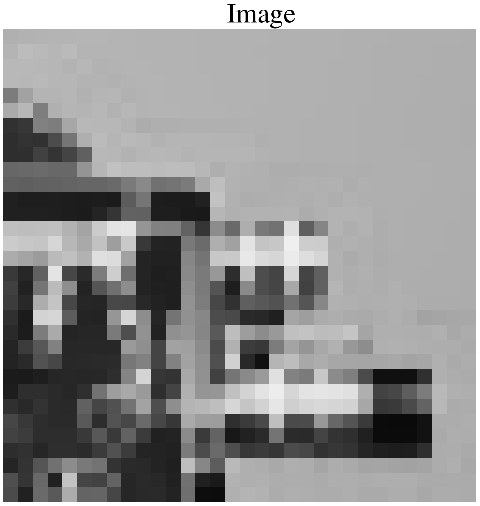
Figure 4 – Input and output images. The rectangle in (a) indicates the selected area to enlarge.


a)Input Image


b)Compressed Background Blurred Not Dilated


c)Compressed Dilated Background Blurred Image


d)Compressed NonEdge Blurred Image Not Dilated


e)Compressed Dilated – Non Edge Blurred Image

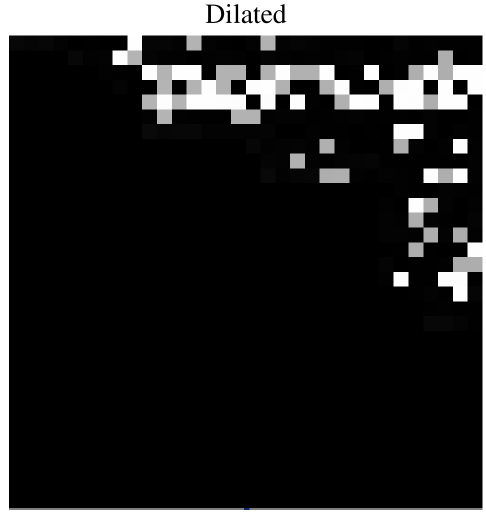

f)| Input Image(a) -Dilated BB Image(c)|

Figure 5-Enlarged portion of Input and Output images.

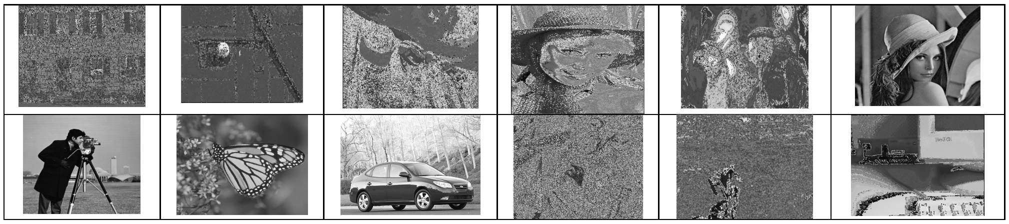


Figure 6 - Test Images (1 to 12 from left to right and top to bottom).

Table I – Bits Per Pixel (bpp) for different compression methods.

Images	Bit Rate	Bit Rate Dilated		% of Area in dilated		Bit Rate Not Dilated	
	JPEG2000	HICBB	HICNB	Foreground	Edges	HICBB	HICNB
1	5.43408	5.42417	5.30674	98.83	88.25	5.42008	5.36306
2	4.16634	3.93496	3.53296	84.97	56.70	3.83663	3.25460
3	3.54374	3.16888	2.55330	71.57	33.00	3.14109	2.55691
4	4.18156	4.03615	3.51434	89.30	55.14	4.01542	3.41170
5	3.51573	2.64545	2.36182	46.16	25.07	2.62144	2.28330
6	4.90051	4.60889	4.68408	70.50	71.01	4.55835	4.71777
7	4.53735	3.88574	3.79480	61.18	49.52	3.86255	3.85339
8	3.74667	3.37915	3.40011	48.59	46.16	3.36198	3.59729
9	5.86682	5.86345	5.83655	96.86	92.68	5.84884	5.92479
10	4.65683	4.29926	4.07089	77.94	61.18	4.24957	4.05032
11	2.28339	1.43876	1.40108	4.45	3.28	1.43465	1.39297
12	2.28880	1.01110	1.03131	3.59	3.41	1.00052	1.02461

Table II - PSNR and CWSSIM for different compression methods.

Images	Similarity Measure Dilated				Similarity Measure Not Dilated			
	PSNR		CWSSIM		PSNR		CWSSIM	
	HICBB	HICNB	HICBB	HICNB	HICBB	HICNB	HICBB	HICNB
1	55.9710	47.2938	0.999997	0.999978	49.9744	32.5744	0.999988	0.999207
2	45.9534	43.5202	0.999938	0.999892	42.5353	36.6147	0.999865	0.999429
3	48.0546	42.0928	0.999978	0.999913	42.9656	35.8153	0.999931	0.999552
4	48.2775	42.3893	0.999978	0.999911	44.0902	34.6182	0.999942	0.999375
5	43.7103	41.6385	0.999949	0.999918	40.9067	36.3809	0.999904	0.999701
6	40.7882	43.2317	0.999864	0.999934	34.6819	35.8589	0.999501	0.999055
7	44.3584	43.9879	0.999962	0.999961	35.3792	36.9884	0.999726	0.998943
8	42.5938	43.509	0.999927	0.999939	38.1663	28.5477	0.999799	0.997322
9	50.0315	50.0794	0.999995	0.999995	41.4667	32.9442	0.999965	0.999718
10	43.7620	42.5542	0.999952	0.999938	38.7022	36.9553	0.999847	0.999574
11	44.0690	43.7894	0.999952	0.999949	42.7493	40.7275	0.999936	0.999883
12	43.0864	44.0542	0.999957	0.999966	41.1857	40.9258	0.999932	0.999923

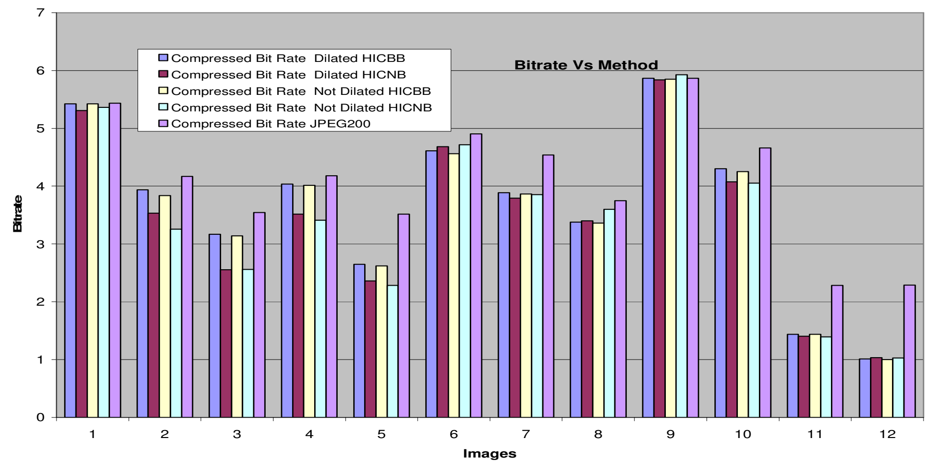


Figure – 7 Chart on Bit rate Vs Compression Methods for different Images

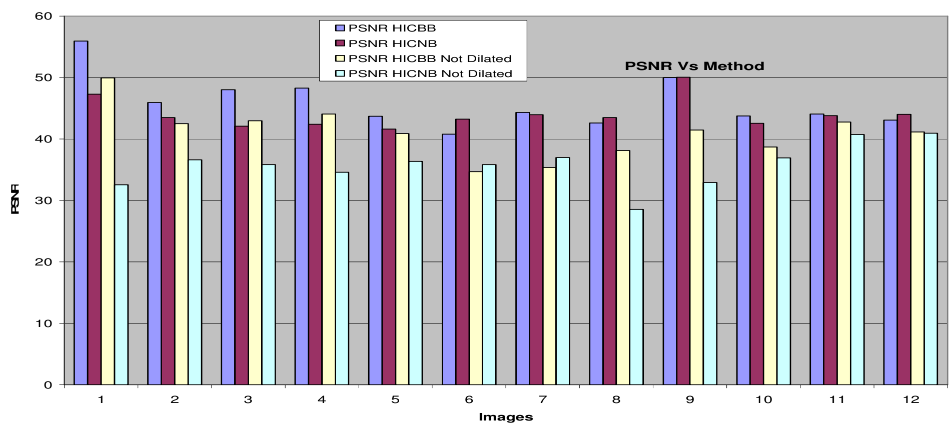


Figure – 8 Chart on PSNR Vs Compression Methods for different Images

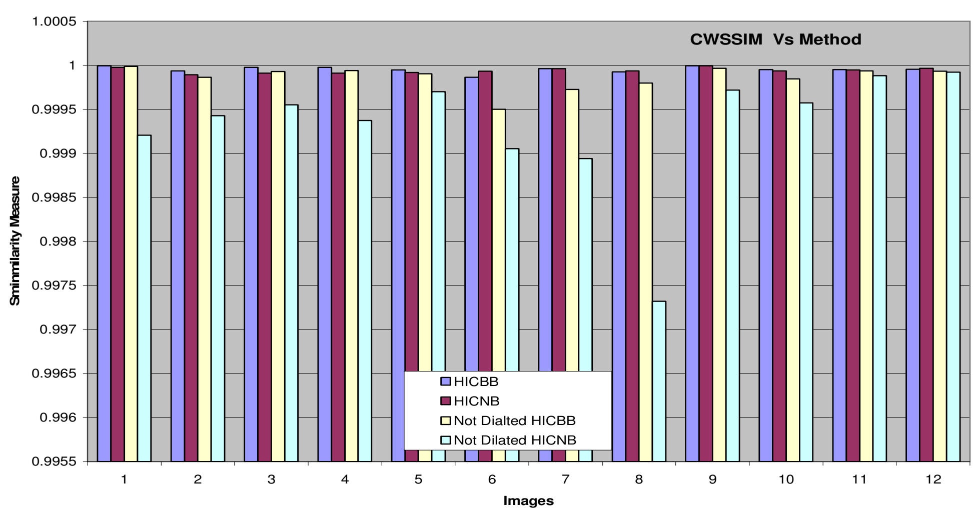


Figure – 9 Chart on CWSSIM Vs Compression Methods for different Images

From figure 5.b and figure 5.d we can find area near the edges is distorted much from the original image, which is caused by the blurring of background and non edge area of the images by HICBB and HICNB correspondingly. The problem of blurring along the edges can be suppressed by an additional step in both HICBB and HICNB. This step of dilation is performed after step 2. The background image is dilated with a structural element (SE) of order 3x3 in HICBB. The edge region is dilated with the SE of same order. With the introduction of dilation operation the distortions are reduced almost completely. This can be observed by comparing figures 4.c, 5.c and figures 4.e, 5.e. According to Marta Mrak *et al.* [2] and [12] PSNR can not be used as definitive picture quality measure. Thus the similarity between the original and decompressed images is computed using CWSSIM [2] and PSNR [4]. The dilation of background image and edges improves PSNR and CWSSIM of the compressed image, visual quality also increased well in both HICBB and HICNB. The bit rate is not much less in non dilated HICBB and HICNB. Thus the HICBB and HICNB can incorporate the dilation operation after step 2. Both HICBB and HICNB are performing well as per the expectation, the bit rate is decreased comparing to lossless compression and similarity is improved comparing to lossy compression [1] [4]. As per the graph in figure 7, it can be observed the HICNB takes fewer bits to represent a pixel comparing to HICBB. By looking at figure 8 and 9 it can be observed that the similarity measure is lesser for HICNB comparing to HICBB.

6. CONCLUSION

In both HICBB, HICNB the bit rate is lesser than lossless compression and quality is higher than lossy compression methods. The computation time is higher than various lossless or lossy compression methods. Among HICBB and HICNB, the later takes higher computation time. The space requirements are also higher for processing than standard lossless compression methods but HICBB and HICNB are taking equal amount of memory resource. The change of smoothing window size affects the compressed bit rate and compressed image quality measures. Higher the window sizes lower the bit rate, PSNR and CWSSIM. From table-II it can be easily observed that the bit rate is also depends on the percentage of area of the foreground of the image and the edges. As the area increases the bit rate also increased since the numbers of pixels to be stored in lossless mode are increased. Since the vital part of the image is preserved, these compression methods can be well suited for any kind of image data store which compresses images offline. Improved segmentation, edge detection and lossless compression methods may be incorporated in future to get better results.

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