Multi-resolution Architecture of Graded Memory

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***Abstract*— An approach to storing static images in some predefined resolution and retrieving stored static images in multi-resolution using multilayer Hopfield neural network is proposed. Here, the Hopfield network is used as a memory, which stores images in predefined resolution. The neural network is trained to store certain number of images. During image retrieval from the network, following schemes are proposed. Firstly, down sampled version of the stored image is provided in some fashion as the query mage, the network initially gives out a coarse image. This coarse output image is processed and fed back as the input image to the memory again. The output image retrieved this time will be better than the one that was obtained initially. This is repeated and the output of the memory becomes better and better as the time progresses. Secondly, the network can be configured to render an image in such a way that the Region Of Interest (ROI) of the image becomes better and better over the period of time. In the third scheme, the network can be configured to render an image with the ROI of the image becoming more blurred over the period of time. The above mentioned schemes have been simulated using MATLAB for the following four images Lena, Baboon, Barbara and Stefan. The results are shown both in the tabular and graphical form.**

Keywords*— *Graded memory, gray scale image storage, Hopfield network, Image retrieval, region of interest(ROI).

I. INTRODUCTION

The image transmission over the bandwidth constrained channel meeting the quality standards is a challenging task. There are many approaches to this end in the literature. The work presented in [2] talk about efficient transmission means for streaming multi-view content over the bandwidth constrained channel. The work presented in [3] explores camera selection in video sensor networks, whereas, the work presented in [4] explores packet scheduling for wireless streaming of multi-view content.

Here a new approach is presented which is a kind of demand based image transmission over the channel. The gray scale image with 256 levels for each pixel requires 8 bits per pixel. In order to represent an image of MxN size with 2^L levels in each pixel, the total number of bits required is MxNxL. To transmit this kind of an image, MxNxL bits are generally compressed using any of the standard compression techniques and transmitted over the channel. The compression technique provides some compression ratio based on the kind of technique used.

If one can compress the image further in some way either by reducing the number of bits in the image before applying the compression technique or after the compression, the number of image bits to be transmitted will reduce further thereby decreasing the load on the channel. Motivated by this, an approach using multilayer Hopfield neural network as a graded memory is analyzed. Graded memory provides a better quality image when a down sampled version of the stored image is presented as an input image. The graded memory works in a multi resolution fashion. The memory stores the image information in some pre-defined resolution during the training of the multilayer Hopfield network. During the image retrieval operation, when the query image is applied as the input to network, the network first gives out some coarse output. The finer details may be synthesized based on the coarse output. The memory starts giving out more and more accurate output with lapse of time, as more and more resolution in the output is requested.

For image storage and retrieval in graded memory, the algorithm presented in [5] is adapted. Due to computer resource issues, initially, the original image of size MxN is partitioned into q number of sub-images. The multilayer Hopfield network [1] of size mxnxL is trained to store q number of these sub-images at a predefined resolution, where, mxn is the size of the partitioned image. For example, if 9 images (q = 9) of size mxn are stored in the network, then, the actual image size is 3mx3n. During image retrieval, when the image(down sampled) with only 3-MSB bits for each pixel (remaining 5 LSB bits of each pixel are made as zeros) is provided as an input image to the network, the memory initially gives out a coarse output image with some resolution. To get higher resolution in the output image, the output image obtained initially is processed and fed back as input to the network. This time, the output of the memory will be better than the one that was retrieved earlier. This can be repeated till the end user is satisfied with the required resolution in the output image.

In applications where one is interested in getting better resolution in the ROI of an image, the graded memory can be configured to render stored image with its ROI getting better and better over the period of time. Whereas, some applications like security require the ROI of an image to be blurred compared to all other regions of the image. In such cases, The graded memory can be configured to render stored image with

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its ROI getting blurred over the period of time compared to other region of the image.

The paper is organized as follows. The section II explains background work of the existing works. Section III elaborates architecture of the graded memory and outlines the simulation setup. Section IV lists research contributions. In section V simulation results are discussed. Section VI summarizes the conclusion.

II. BACKGROUND

It is possible to get multi-resolution images of an image using wavelet decomposition, but, it is not flexible in controlling the PSNR of the multi-resolution images thus obtained. Whereas, the work proposed here is more flexible and an image with appropriate PSNR can be obtained by rendering the required number of MSB bits per pixel from the retrieved image.

This work is in continuation of the work presented in [6] and [7]. The concept of graded memory is explained in detail in [6] and [7], where, the use of the Hopfield network as graded memory is emphasized along with various structures of Hopfield network namely, torus, non torus and fully connected along with their performance in image storage and retrieval. It turns out that the graded memory connected in fully connected fashion yields better image storage and retrieval compared to the other two structures. But, the number of connection weights are also huge in fully connected network compared to the other two structures.

The gray scale image storage of size MxN with 2^L gray levels for each pixel using multilayer Hopfield neural network as presented in [5] uses torus connection. There, the Hopfield network is used as a binary associative memory to retrieve the original image by providing a noisy version of the image as the input. Before storing the image, the image with its gray scale binary values are converted to an image with grey code values. The image thus obtained is partitioned into sub-images and the Hopfield network is trained to store these sub-images. During image retrieval, Gaussian noise is added to the test image and the retrieved image is compared with the stored. It is found out that, the image thus retrieved matches exactly with the stored.

III. ARCHITECTURE OF GRADED MEMORY

The graded memory architecture consists of multilayer Hopfield neural network with nodes located in three dimensions. The training algorithm used to train the network is adapted from [5]. Equation related to asymmetrical connection weights are used here. To store a gray scale image of size MxN with 2^L gray levels, the network uses MxNxL nodes, where, M is the number of rows, N the number of columns and 2^L is number of gray scale levels for each pixel. The network used here is fully connected with each node having connections to its nearest neighbor nodes decided by r and s in both horizontal and vertical directions respectively. Whereas, [5] uses nearest neighborhood value of 3 for r and s, here a value of 4 is used for better image retrieval. This increases the total number of connection weights between network nodes. The detailed description of how the graded memory is trained and tested is presented in [6] and [7].

The block diagram of the graded memory is shown in fig. 1. Initial query image is the down sampled version of the stored image in the Hopfield network. The delay is involved in processing the output image which is marked as data. A Hopfield network of size MxNxL can store more than one image. It is observed that, it can store 25 images of size 16x16 in fully connected fashion and be able to recall all these images with acceptable MSE and PSNR, when the network is fed back with the retrieved output image repeatedly.

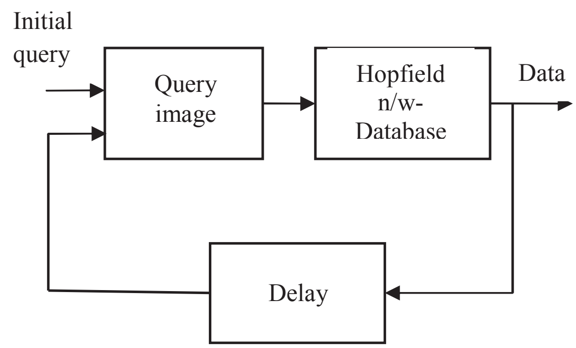


Fig. 1. Graded memory block diagram

The graded memory is simulated using MATLAB 2012. The multilayer Hopfield neural network training algorithm as presented in [5] is adapted & is coded in MATLAB. The image retrieval algorithm is also coded in MATLAB. The network is trained for the images Lena, Baboon, Barbara and Stefan as shown in fig. 2, and tested. The simulation results are provided in section V.

Fig. 2. Images used for training the neural network

The three schemes that are proposed during image retrieval from the graded memory are explained below.

A. Image retrieval from down sampled image

When the end user wants demand based quality in the image, the graded memory can be configured to work in this fashion. When a better quality image is requested, then, the graded memory is provided with an input image having more MSB bits per pixel during image retrieval. So, the more the requested resolution in the output image, the more the number of MSB bits in the input image per pixel provided to the graded memory. This is tested for input image with 3-MSB bits/pixel, 4-MSB bits/pixel and so on till 7-MSB bits/pixel.

B. Image retrieval with better ROI in the image

The graded memory can be configured to render an output image with good resolution in ROI of the image only. In this case, the ROI of the image will have better resolution compared to other regions of the image. Here, the memory gives out all 8 bits per pixel in ROI of the image, whereas, only the required number of MSB bits per pixel in all other region other than ROI. The number of MSB bits per pixel in region other than ROI is configurable and can take values from three to eight MSB bits, based on the users requirement. The results shown here have 4 MSB bits in region other than ROI.

C. Image retrieval with blurred ROI in the image

Graded memory can be configured to get an image with blurred ROI. In this case, the image that is rendered from the memory will have less MSB bits per pixel in the ROI of the image, whereas, all other region of the image other than ROI contains all eight bits per pixel. When provided with the query image, the graded memory initially gives out an image with ROI in the image having poor resolution compared to the region other than the ROI of the image. This is done by rendering four-MSB bits only per pixel in the ROI of image and all eight bits per pixel in other region of the image. The number of MSB bits per pixel in the ROI is configurable and can take values from three to eight MSB bits. In the example show here, memory is configured for four MSB bits per pixel.

IV. RESEARCH CONTRIBUTIONS

Derived a mechanism to use multilayer Hopfield neural network as a graded memory. Simulated graded memory using multilayer Hopfield neural network. The code for simulating the neural network is written in MATLAB. Graded memory stores multiple images in predefined resolution. Retrieval of stored images in multiple abstraction levels based on the end user's demand. Arrived at a mechanism to generate images of multiple abstractions by selecting number of bits per pixel appropriately. When all bits are rendered, an image with maximum resolution is obtained. Reducing the number of bits rendered reduces the image resolution non linearly.

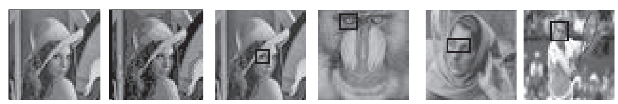
Simulated image retrieval from graded memory with the ROI of the stored image getting better and better compared to the other region of the image. This is done by rendering varying number of bits per pixel in the ROI of the image and fixed number of bits in the rest of the region of the image.

Simulated image retrieval from graded memory with the ROI of the stored image getting blurred relative to other region of the image over the period of time. This is done by rendering fixed number of bits in ROI and variable number of bits in other region.

V. SIMULATION RESULTS

The graded memory is tested for Lena, Baboon, Barbara and Stefan images. When it is configured for normal operation, during the training, an image of size 48x48 of Lena is taken and partitioned into 9 sub-images each of size 16x16 pixels. The network of size 16x16x8 is trained to store all these 9 images. The nearest neighborhood parameters r and s are set to a value of 4. The learning rate value is set to 1. During image retrieval, the down sampled version of these 9 sub-images is got by making 5 LSB bits of each pixel to 0 value and retaining 3 MSB bits of each pixel to original value. Fig. 3(a) and Fig. 3(b) show the original LENA image of size 48x48 and the down sampled image respectively.

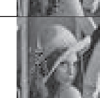
Table I shows the input and the output images of the memory along with the PSNR values with respect to the original input image. First row of the table I shows the output image of the memory containing only four MSB bits and other four LSB bit values set to zero, when down sampled input image is provided as the input. The down sampled image thus provided as input contains three MSB bits per pixel retaining their values and all other bits set to zero. The down sampled version of Lena is as shown in fig. 3 (b). Similarly, subsequent rows show the output of the memory when the output obtained in previous row is fed as the input image along with the valid number of MSB bits. It is observed that the memory is able to retrieve the original image eventually or a better image with good PSNR.



(a) (b) (c) (d) (e) (f)

Fig. 3. (a) Original LENA 48x48 image. (b) Down sampled LENA image. (c) LENA image with ROI on the right eye. (d) Babbon image with ROI on right eye. (e) Barabara image with ROI covering both eyes. (f) Stefan image with ROI on the face.

TABLE I. IMAGE RETRIEVAL FROM DOWN SAMPLED LENA

Input		Output		
Bits/pixel	***Image***	***Bits/pixel***	***Image***	***PSNR (dB)***
3		4		26.55
4		5		27.81
5		6		30.15
6		7		31.78
7		8		Infinity

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Similarly, Table II, III and IV show the results for Baboon Barbara and Stefan images respectively.

TABLE II. IMAGE RETRIEVAL FROM DOWN SAMPLED BABOON

Input		Output		
Bits/pixel	*Image*	*Bits/pixel*	*Image*	*PSNR (dB)*
3		4		26.23
4		5		30.28
5		6		38.68
6		7		51.09
7		8		Infinity

TABLE III. IMAGE RETRIEVAL FROM DOWN SAMPLED BARBARA

Input		Output		
Bits/pixel	*Image*	*Bits/pixel*	*Image*	*PSNR (dB)*
3		4		21.95
4		5		25.58
5		6		32.07
6		7		44.15
7		8		74.80

TABLE IV. IMAGE RETRIEVAL FROM DOWN SAMPLED STEFAN

Input		Output		
Bits/pixel	*Image*	*Bits/pixel*	*Image*	*PSNR (dB)*
3		4		20.48
4		5		20.98
5		6		22.43
6		7		24.55
7		8		28.16

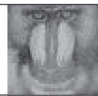
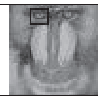
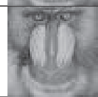
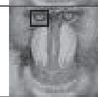
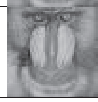
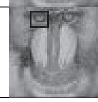
When the graded memory is configured to render better resolution in the ROI of the image, the memory gives the image with good resolution in ROI of the image. Table V shows the results obtained in this case. In this table, the down sampled input images, the output images along with the PSNR values for the output image and PSNR in the ROI region are provided. It is clear that the ROI region is getting better and better compared to the overall image. Here also the output image given by the memory matches to the original image with very good PSNR. ROI is marked with rectangular box in the Lena, Baboon, Barbara and Stefan images, which are shown in Fig. 3(c), 3(d), 3(e) and 3(f) respectively. Table VI, VII and VIII show the results for Baboon, Barbara and Stefan images respectively.

TABLE V. IMAGE RETRIEVAL WITH BETTER ROI IN LENA

Input		Output			
Bits/pixel	*Image*	*Bits/pixel*	*Image*	*PSNR (dB)*	
				Image	*ROI*
3		***4***		***26.60***	***33.25***
4		***4***		***27.17***	***34.95***
5		***4***		***29.47***	***34.96***
6		***4***		***29.50***	***42.21***
7		***4***		***29.50***	***51.17***

TABLE VI. IMAGE RETRIEVAL WITH BETTER ROI IN BABOON

Input		Output			
Bits/pixel	*Image*	*Bits/pixel*	*Image*	*PSNR (dB)*	
				Image	*ROI*
3		4		26.24	21.38
4		4		28.74	30.21

Input		Output			
Bits/pixel	*Image*	*Bits/pixel*	*Image*	*PSNR (dB)*	
				Image	*ROI*
5		4		29.20	35.22
6		4		29.24`	42.22
7		4		29.25	50.46

When the graded memory is configured to render lower resolution in the ROI of the image, the memory gives the image with poor resolution in ROI of the image. Table IX shows the results obtained in this case. In this table, the down input sampled images, the output images along with the PSNR values for the output image and PSNR in the ROI region are provided. It is clear that the ROI region has lower PSNR values compared to the PSNR obtained for the overall image. In this case, four MSB bits/pixel are only considered in the ROI of the image. Table X, XI and XII show the results for Baboon, Barbara and Stefan images respectively.

From the results plotted in fig. 4, fig.5, fig.6 and fig.7, it is clearly observed that the graded memory is able to provide multi-resolution output image when provided with an input of some predefined resolution. The resolution in the output image improves when the output image retrieved in the previous iteration is provided as input. Continuing this, and if one can afford to wait, the output image of high resolution can be obtained from the graded memory. The memory is also able to render an image with improving resolution in the ROI of the image compared to other region of the image. It is able to render an image with low resolution in the ROI and high resolution in the other region of the image.

It is observed that the graded memory works in multi-resolution fashion correctly when it stores images with their histograms following normal distribution compared to images with histograms of other distributions.

TABLE VII. IMAGE RETRIEVAL WITH BETTER ROI IN BARBARA

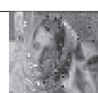
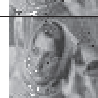
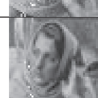
Input		Output			
Bits/pixel	*Image*	*Bits/pixel*	*Image*	*PSNR (dB)*	
				Image	*ROI*
3		4		21.64	26.43
4		4		24.50	30.32
5		4		27.94	38.21
6		4		29.37	infinity
7		4		29.47	Infinity

TABLE VIII. IMAGE RETRIEVAL WITH BETTER ROI IN STEFAN

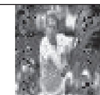
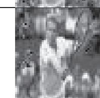
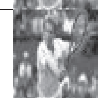
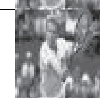
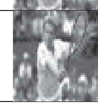
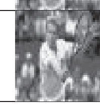
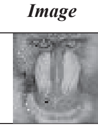
Input		Output			
Bits/pixel	*Image*	*Bits/pixel*	*Image*	*PSNR (dB)*	
				Image	*ROI*
3		4		20.50	31.48
4		4		25.02	Infinity
5		4		28.93	Infinity
6		4		29.39	Infinity
7		4		29.39	Infinity

TABLE IX. IMAGE RETRIEVAL WITH BLURRED ROI IN LENA

Input		Output			
Bits/pixel	*Image*	*Bits/pixel in ROI*	*Image*	*PSNR (dB)*	
				Image	*ROI*
3		4		29.60	27.58
4		4		30.95	29.63
5		4		44.96	29.63
6		4		45.19	29.63
7		4		45.19	29.63

TABLE X. IMAGE RETRIEVAL WITH BLURRED ROI IN BABOON

Input		Output			
Bits/pixel	*Image*	*Bits/pixel in ROI*	*Image*	*PSNR (dB)*	
				Image	*ROI*
3		***4***		***29.07***	***25.81***

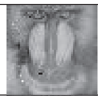
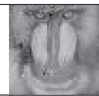
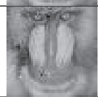
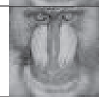
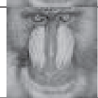
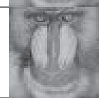
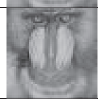
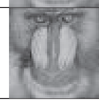
Input		Output			
Bits/pixel	*Image*	*Bits/pixel in ROI*	*Image*	*PSNR (dB)*	
				Image	*ROI*
4		***4***		***31.29***	***26.61***
5		***4***		***39.12***	***28.80***
6		***4***		***44.36***	***28.80***
7		***4***		***44.36***	***28.80***

TABLE XI. IMAGE RETRIEVAL WITH BLURRED ROI IN BARBARA

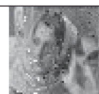
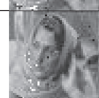
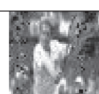
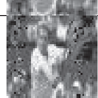
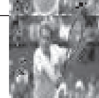
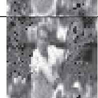
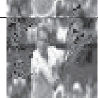
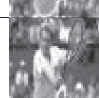
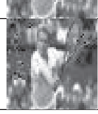
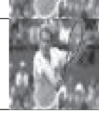
Input		Output			
Bits/pixel	*Image*	*Bits/pixel in ROI*	*Image*	*PSNR (dB)*	
				Image	*ROI*
3		4		21.92	23.77
4		4		25.47	27.26
5		4		31.96	29.1
6		4		40.72	29.1
7		4		42.77	29.1

TABLE XII. IMAGE RETRIEVAL WITH BLURRED ROI IN STEFAN

Input		Output			
Bits/pixel	*Image*	*Bits/pixel in ROI*	*Image*	*PSNR (dB)*	
				Image	*ROI*
3		4		21.40	27.81
4		4		27.23	29.63
5		4		37.75	29.63
6		4		42.42	29.63
7		4		42.42	29.63

VI. CONCLUSION

The graded memory is able to provide multi-resolution images when a down sampled image of the stored images is provided as the input. The memory is also able to render an image with improving resolution in the ROI of the image compared to other region of the image. It is able to render an image with low resolution in the ROI and high resolution in the other region of the image.

Graded memory can store multiple images. Here 9 images, each of size 16x16 are stored in Hopfield neural network of size16x16x8. Although it can store multiple images, the limitation of the graded memory is that it requires huge number of connection weights. To reduce the number of connection weights, following few options can be looked at. First option is to store only the four MSB bits of the total eight bits per pixel for the whole image thereby, reducing the L value from 8 to 4 which in turn reduces the number connection weights by half. Since four LSB bits per pixel are not stored in the memory, during the retrieval of the image, a binary value of 1000 (decimal value of 8) is appended to the retrieved four MSB-bits for each pixel as LSB bits. This will introduce an error of ±8 grey scale value to each pixel compared to the original value. This reduces the image quality to some extent which many applications can manage with. Second options is to split the bigger network into multiple smaller networks and then store the image in multiple networks. Third option is to combine both first and second option which will further reduce the number of connection weights.

The second limitation is that when multiple sub-images of the image are stored in the network and if these sub-images are similar, it is not possible to retrieve sub-images with good PSNR values. In such a case, constructed image may not match closely with the stored image. The third limitation is that an image with improper distribution of grey levels over the pixels will not be retrieved correctly.

Some of the applications of the graded memory are in the area of image search, security applications and real time video transfer meeting QOS requirements.

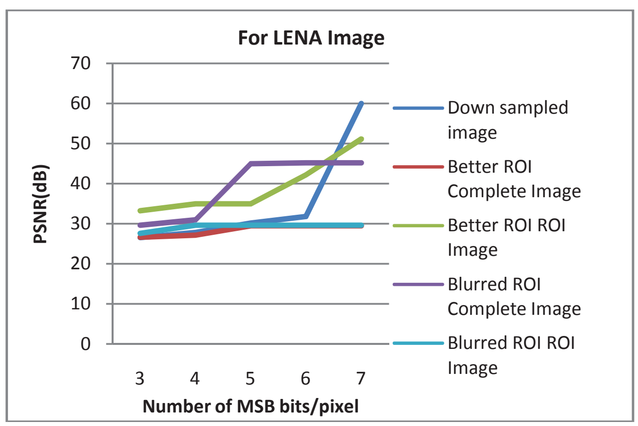


Fig. 4. Graph showing relationship between the numberr of bit/pixel provided as input to memory and the the output resolution in PSNR for LENA image

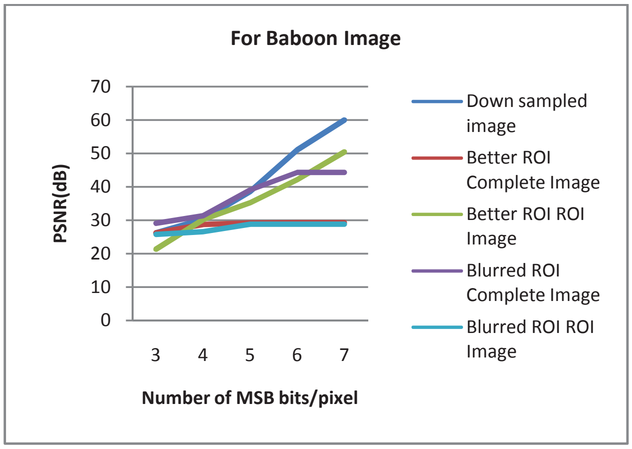


Fig. 5. Graph showing relationship between the numberr of bit/pixel provided as input to memory and the the output resolution in PSNR for Baboon image

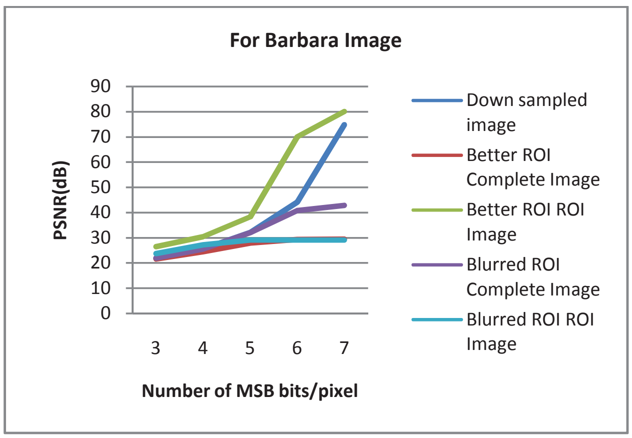


Fig. 6. Graph showing relationship between the numberr of bit/pixel provided as input to memory and the the output resolution in PSNR for Barbara image

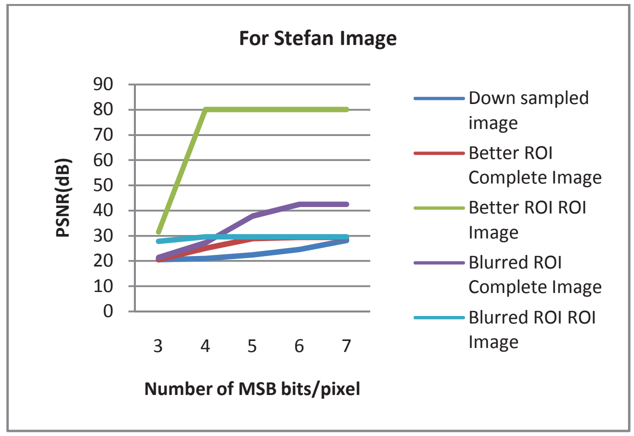


Fig. 7. Graph showing relationship between the numberr of bit/pixel provided as input to memory and the the output resolution in PSNR for Stefan image

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