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Image Compression using Side Match Vector Quantization Technique

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Abstract: *The field of Image processing makes a high impact in the era of fast growing technology to increase or to satisfy the human comfort level. A single image may contain thousand times more information than a written text on piece of paper. But due to the advent of technology, number of image formats exists to provide strength to the image data like JPEG, Tiff, BMP, Gif etc. Due to this change in technology and the existence of these different formats, high resolution images are produced and require more memory for the purpose of storage. Even when we want to communicate on the basis of these images through Internet for some purpose then the issue arises and affect the communication. To deal with this issue some compression mechanism is required. In case of Image procession we can either have lossless image compression or lossy image compression. In this paper a lossless technique of Image processing is proposed by considering Haar wavelet and Vector transform techniques. 97% compression percentage is achieved with the help to proposed method and when the results are compared with other techniques low SNR values and high RMSE values are achieved for the proposed system which shows its accurate behaviour.*

Keywords: *Image processing, lossless compression, lossy compression, Haar wavelet and Vector transform*

I. INTRODUCTION

Image compression is a field where an original image is reduced to a smaller sized image and then for the purpose of remote communication this reduced image is used. At the receiver side, this reduced image is again converted to original image by the implementation of some algorithms. The result of these algorithms produces another image which may be very close to the original one. Image compression procedure is not similar as the compression of raw data. The process followed in both the cases is similar but in case of images certain statistical properties affect the overall process and create some challenges at the stage of decompression. During the process of decompression to get the original image back some of the finer details in the image sometime have to be sacrificed for saving a little more bandwidth or storage space etc. This also means that lossy compression techniques can be used in this area. Loss less compression process always produces the replica of the original image after decompression stage. Lossless techniques are required in the case of sensitive data applications such as legal documents, executable documents, medical images etc. For example, in case of compression of audio recording the silence can be replaced by some value which indicates how long that silence was present in the audio. Similarly, the number of white spaces can replace different white spaces present in the image. Data compression process is mostly used to decreases the size of the data to deal with less storage and low band width requirement issues. To increase the overall throughput various communications equipment like modems, bridges, and routers use different compression techniques which was not there previously in case of standard phone lines or leased lines. Compression is also used to compress voice telephone calls transmitted over leased lines so that more calls can be placed on those lines. In case of video conferencing applications compression is the main weapon to deal with the issues like lesser bandwidth networks and high speed networks. Compression techniques show promising results in the application where voice and data are combined to form data packets. Compression techniques have been developed that reduce the data requirements for a voice channel down to 8Kbits/sec. This is a significant improvement over non compressed voice (64 Kbits/sec) and older compression techniques yielding 32 Kbits/sec. During image compression process a digital image is considered as a matrix containing intensity values of different image pixels as the data stored inside the matrix. The intensity values in case of Gray scale images is in the range of 0-255 means the stored inside the matrix can have minimum value as 0 and maximum value as 255. All the mathematical methods for the sake of compression only consider this intensity data as raw data. To give strength to compression process linear algebra techniques are used. These techniques also help to maintain a suitable level of detail present in the image. The field of Medical image processing involves in the task of processing finer details hidden in the medical images. These details may affect the treatment process of any medical person and may provide a specific direction to work. But again when different medical persons present at remote locations, wants to share some information in the form of medical images my face the difficulty due to the size of image. The size of image may become a barrier in front of limited bandwidth channels. Here, to deal with this issue, a hybrid lossless image compression algorithm is presented in this paper. This

algorithm is the combination of Haar wavelet technique and Vector transform technique. The proposed system of compression and decompression is also compared with the existing algorithms such as Integer to Integer compression and Band-let compression techniques. The system produces better results than existing algorithms. The next part of the paper will give a highlight to the work already done by other researchers in this field and after that there is a discussion about the existing techniques used for the purpose of comparison. Then the proposed technique is explained in detail. At the end results obtained from the proposed system are explained with the help of tables and charts.

II. LITERATURE SURVEY

A. Image Compression Techniques

An image 2048 pixel (2048 pixel *2048 pixel *24 bit) , without compression would require 13 MB of storage and 32 second of transmission, utilizing a high speed , 4 mbps, ISDN line. If the image is compressed at a 20:1 compression ratio, the storage requirement is reduced to 625 KB and the transmission time is reduced to less than 2 seconds. Image files in an uncompressed form are very large, and the internet especially for people using a 1mps or 2mps dialup modem, can be pretty slow. This combination could seriously limit one of the web's most appreciated aspects – its ability to present images easily.

B. Huffman Coding

Huffman algorithm is developed for compressing of text; it was developed by David A. Huffman and published in the 1952 paper "A Method for the Construction of Minimum-Redundancy Codes". The idea of Huffman codes is to encode the more frequently occurring characters with short binary sequences, and less frequently occurring ones with long binary sequences. Depending on the characteristics of the file being compressed it can save from 20% to 90%. The Huffman codes take advantages when not all symbols in the file occur with same frequency [5].

C. Characteristic to judge Compression Algorithm

Image quality describes the fidelity with which an image compression scheme recreates the source image data. There are four main characteristics to judge image compression algorithms. These characteristics are used to determine the suitability of a given compression algorithm for any application.

1) *Compression Ratio*: The compression ratio is equal to the size of the original image divided by the size of the compressed image. This ratio gives how much compression is achieved for a particular image. The compression ratio achieved usually indicates the picture quality. Generally, the higher the compression ratio, the poorer the quality of the resulting image. The tradeoff between compression ratio and picture quality is an important factor to consider when compressing images. Some compression schemes produce compression ratios that are highly dependent on the image content. This aspect of compression is called data dependency. Using an algorithm with a high degree of data dependency, an image of a crowd at a football game (which contains a lot of detail) may produce a very small compression ratio, whereas an image of a blue sky (which consists mostly of constant colors and intensities) may produce a very high compression ratio [6].

$$CR = \text{(Amount of original data)} / \text{(Amount of compressed data)} \quad (1)$$

$$CR\% = (1 - (1/CR)) * 100 \quad (2)$$

Where CR is compression rate, CR% is compression ratio in percentage.

2) *Compression Speed*: Compression time and decompression time are defined as the amount of time required to compress and decompress a image, respectively. Their value depends on the following considerations:

- The complexity of the compression algorithm.
- The efficiency of the software or hardware implementation of the algorithm.
- The speed of the utilized processor or auxiliary hardware.

Generally, the faster that both operations can be performed, the better. Fast compression time increases the speed with which material can be created. Fast decompression time increases the speed with which the user can display and interact with images [].

3) *Mean Square Error*: Mean square error measures the cumulative square error between the original and the decompressed image.

The formula for mean square is given as:

$$MSE = \frac{1}{N} \sum_{i=1}^N [\hat{f}(i, j) - f(i, j)]^2 \quad (3)$$

Where N is the size of the image, MSE is Mean Square Error, $\hat{f}(i, j)$ and $f(i, j)$ are the matrix element of the decompressed and the original image at (i, j) pixel

4) *Peak Signal to Noise Ratio*: Peak signal to reconstructed image measure known as PSNR (Peak signal-to-noise ratio)

$$\text{PSNR} = 10 \log_{10} \left| \frac{I^2}{MSE} \right| \quad (4)$$

Here signal is the original image and noise is the error in reconstructed image. In general, a good reconstructed image is one with low MSE and high PSNR. That means that the image has low error.

D. *Lossless and LOSSY Compression*

There are two types of image compression they are called lossy and lossless. Lossless image compression is one of the preferred once and it is used for medical images, architectural designs and clipart. The reason is that lossless can be converted to its original replica after compression without losing any data from the image [5]. Second, lossy image compression is unnoticeable data loss in the image data which is called visually lossless. The data that has been lost is not visually noticeable to naked eye.

1) *Lossless Compression*: It is generally used for applications that cannot allow any difference between the original and reconstructed data.

- a) Run Length Encoding [7].
- b) Arithmetic Coding [8] & [9].
- c) Lempel- Ziv - Welch (LZW) Encoding and
- d) Chain Codes

2) *Lossy Compression*: Lossy compression techniques involve some loss of information, and data cannot be recovered or reconstructed exactly. In some applications, exact reconstruction is not necessary. For example, it is acceptable that a reconstructed video signal is different from the original as long as the differences do not result in annoying artefacts.

- a) Quantization [11].

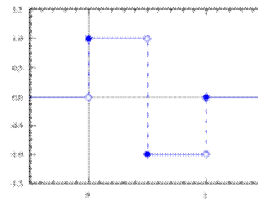
E. *The Use Of Neural And Wavelet Techniques For Image Compression*

With the growth of multimedia and internet, compression techniques have become the thrust area in the fields of computers. Multimedia combines many data types like text, graphics, images, animation, audio and video. In [17] back propagation neural network training algorithm has been used for image compression. Back propagation neural network algorithm helps to increase the performance of the system and to decrease the convergence time for the training of the neural network. In [17] an adaptive method for image compression based on complexity level of the image and modification on levenberg-marquardt algorithm for MLP neural network learning is used. In adaptive method different back propagation artificial neural networks are used as compressor and decompressor and it is achieved by dividing the image into blocks, computing the complexity of each block and then selecting one network for each block according to its complexity value. The proposed algorithm has good convergence. This method reduces the amount of oscillation in learning procedure. Multilayer neural network (MLP) is employed to achieve image compression. The network parameters are adjusted using different learning rules for comparison purposes. Mainly, the input pixels will be used as target values so that assigned mean square error can be obtained, and then the hidden layer output will be the compressed image. It was noticed that selection between learning algorithms is important as a result of big variations among them with respect to convergence time and accuracy of results. After decomposing an image using the discrete wavelet transforms (DWT), a neural network may be able to represent the DWT coefficients in less space than the coefficients themselves [16]. After splitting the image and the decomposition using several methods, neural networks were trained to represent the image blocks. By saving the weights and bias of each neuron, an image segment can be approximately recreated. Compression can be achieved using neural networks. Current results have been promising except for the amount of time needed to train a neural network. Image compression is now essential for applications such as transmission and storage in data bases. [2] Review and discuss about the image compression, need of compression, its principles, and classes of compression and various algorithm of image compression. [2] Attempts to give a recipe for selecting one of the popular image compression algorithms based on Wavelet, JPEG/DCT, VQ, and Fractal approaches. He reviews and discusses the advantages and disadvantages of these algorithms for compressing gray scale images, give an experimental comparison on 256×256 commonly used image of Lena and one 400×400 fingerprint image. The need for an efficient technique for compression of Images ever increasing because the raw images need large amounts of disk space seems to be a big disadvantage during transmission & storage. Even though there are so many compression techniques already present a better technique which is faster, memory efficient and simple surely suits the requirements of the user. [5] proposed the Lossless method of image compression and decompression using a simple coding technique called Huffman coding. This technique is simple in implementation and utilizes less

memory. A software algorithm has been developed and implemented to compress and decompress the given image using Huffman coding techniques in a MATLAB platform.

F. Haar Wavelet

In mathematics, the Haar wavelet is a certain sequence of functions. It is now recognized as the first known wavelet. This sequence was proposed in 1909 by Alfred Haar. Haar used these functions to give an example of a countable orthonormal system for the space of square integrable functions on the real line. The study of wavelets, and even the term "wavelet", did not come until much later. The Haar wavelet is also the simplest possible wavelet. The technical disadvantage of the Haar wavelet is that it is not continuous, and therefore not differentiable.



The Haar wavelet's mother wavelet function $\psi(t)$ can be described as

$$\psi(t) = \begin{cases} 1 & 0 \leq t < 1/2, \\ -1 & 1/2 \leq t < 1, \\ 0 & \text{otherwise.} \end{cases}$$

and its scaling function $\phi(t)$ can be described as

$$\phi(t) = \begin{cases} 1 & 0 \leq t < 1, \\ 0 & \text{otherwise.} \end{cases}$$

The Haar wavelet operates on data by calculating the sums and differences of adjacent elements. The Haar wavelet operates first on adjacent horizontal elements and then on adjacent vertical elements. The Haar transform is computed using:

$$\frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

III. EXISTING SYSTEM

A. Image Compression using Neural Network

- 1) *Pre-Processing:* Designing of image compression system includes two stages. These are training and testing stages. In training stage the synthesis of image compression system have been carried out. Image compression system includes three basic blocks. These are pre-processing, compression using NN block and reconstruction (decompressing) steps. Pre-processing performs the preparing input-output data for NN. These are segmentation of image into input subsections and transforming these subsections into gray values. Image gray values are scaled in interval (0) and (1). These data are used to organise input and output training data for NN. Second block is neural networks. Three layers feed forward neural networks that includes input layer, hidden layer, and output layer is used. Back propagation algorithms had been employed for the training processes. The input prototypes and target values are necessary to be introduced to the network so that the suitable behaviour of the network could be learned. The idea behind supplying target values is that this will enable us to calculate the difference between the output and target values and then recognize the performance function which is the criteria of our training. For training of the network, the different images of size 256x256 pixels had been employed. In this paper, in pre-processing step, the original image, to be used, is divided into 4x4 pixel blocks. Each block is reshaped into a column vector of 16x1 elements. Here we derive 4096 blocks for the image. 16x4096 matrixes have been formed. Here each column represented one block. For scaling purposes, each pixel value should be divided by 255 to obtain numbers between (0) and (1).
- 2) *Post-Processing:* After training, the derived network represents the compressed images. The NN is represented by weight coefficients. In the next step reconstruction of image will be performed. The aim is to display output matrices representing image sections. This can be done by reshaping column into a block of the desired size and then arrange the blocks to form the image again. In the output layer, each column is reshaped into 4x4 pixel blocks as the input. Each pixel value is multiplied by 255 to obtain the original gray level value of the pixels.

B. Image Compression Using Haar Wavelet Transform

- 1) *Procedure:* Compression is one of the most important applications of wavelets. Like de-noising, the compression procedure contains three steps:
 - a) *Decomposition:* Choose a Haar Wavelet; choose a level N. Compute the wavelet decomposition of the signal at level N.
 - b) *Threshold Detail Coefficients:* For each level from 1 to N, a threshold is selected and hard thresholding is applied to the detail coefficients.
 - c) *Reconstruct:* Applying Inverse Haar Wavelet reconstruction using the original approximation coefficients of level N and the modified detail coefficients of levels from 1 to N.
- 2) *Algorithm:* Discrete Wavelet Transform (DWT) is used to decompose the images into approximate and detail components. Two-dimensional DWT leads to a decomposition of approximation coefficients at level j in four components: the approximation at level j + 1, and the details in three orientations (horizontal, vertical, and diagonal).

The input image $cA_0 = S$ is initialized for the decomposition. After decomposition the approximate and detail components will be derived. Decomposition could be done several times. For $j=2$, the two – dimensional wavelet tree has the following form

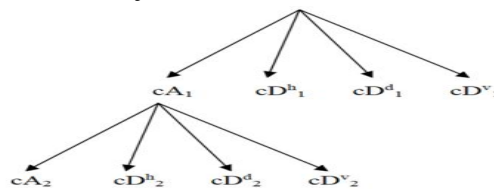


Fig 1 Two Dimensional DWT

IV. PROPOSED SYSTEM

A. Haar Wavelet Technique

In this paper a hybrid technique is proposed using Haar wavelet technique and Vector transform. The proposed technique is fit for both lossless and lossy image compression. During this technique the average values of consecutive pixels and the difference is used for the purpose of compression. These operations produce a sparse matrix. In a sparse matrix large portion of its entries are 0. A sparse matrix can be stored in a smaller file sizes. The basic method is to start with an image, which can be regarded as an $m \times n$ matrix with values 0 to 255. The algorithm works on intensity values of the image as follows: Suppose $r = [220\ 180\ 248\ 108\ 126\ 142\ 160\ 160]$ is one row of an 8x8 image matrix. Following are the set of operations during the execution of the proposed algorithm:

- 1) Make four different pairs of the entries of set r as (220,180),(248,108),(126,142),(160,160).
- 2) Form the average of each pair as $(220+180)/2= 200$ and at the end get the set of four values as [200, 178, 134, 160]. This new set is denoted by r1 and it is a new vector formed.
- 3) In this step, subtract each average value obtained in the previous step from the first entry of the pair which was used to form this value. As for the pair (220,180), average value is 200 and the new value is $(220-200=20)$. So, for r1 vector its next values are (20, 70, -8, 0). After this step vector r1 is (200, 178, 134, 160, 20, 70, -8, 0). The first four values of r1 are called approximation coefficients and the last four are called detailed coefficients.
- 4) Similarly the same steps are followed in the same order by making the pairs of approximation coefficients and generate detailed coefficients from it up to the possible level.
- 5) Reverse steps will provide the decompressed image.

V. IMPLEMENTATION

A. Side Match Vector Quantization

Since side match vector quantization (SMVQ) provides better image quality of reconstructed image and compression bit rate than vector quantization (VQ) does, it becomes another choice to compress the transmitting images when the bandwidth is limited. To expand the cover media for transmitting confidential information, we propose a novel data hiding scheme which embeds secret data into the SMVQ-compressed image. In terms of the payload capacity, the visual quality, and the compression rate, experimental results confirm that the performances of our scheme are better than that of other information hiding schemes for VQ-based and SMVQ-based compressed images. In addition, the embedded secret data can be extracted from the stego-image without referencing the original cover image.

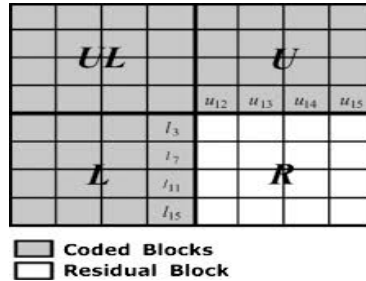


Fig 2: Code block and residual block

Side match vector quantization provide

Change original seed blocks. More seed blocks or “cross” blocks. Then residual blocks can be recovered by comparing with sides of its upper, right, down, and left blocks.

- 1) We recover every residual block in advance. Compare with corresponding blocks in original image. When its distortion is over predetermined threshold, then encode the block in usual way.
- 2) The SMVQ algorithm tries to make the gray level transition across the boundaries of the vectors as soon as possible. In our experiments, the improvement using SMVQ to recover the lost blocks is up to 3.618 dB for the image Lena. An interleaved SMVQ (ISMVQ) algorithm is also proposed in this paper. The ISMVQ algorithm combines the VQ algorithm and the SMVQ algorithm. In our experiments, the improvement of ISMVQ over VQ is up to 1.488 dB at the same bit-rate for the image Lena.

B. SMVQ for Image Coding

- 1) **Encoding Process:** As mentioned in previous section, SMVQ takes advantage of both the redundancy within a block and strong correlation between the neighboring blocks for high quality image coding at low bitrates. The original SMVQ encodes each image block by a smaller-sized state codebook generated from a master codebook using a side-match selection function as shown in Figure 1. Assume that the master codebook has N code words with each codeword an $m \times n$ vector denoting by $C_i, i=1, 2, \dots, N$. Also assume that the image to be encoded is partitioned into blocks of size $m \times n$. SMVQ encodes the image blocks in an order from left to right and top to bottom. For each block being encoded, SMVQ uses the side information of its upper and left neighboring blocks to produce the state codebook. The block is encoded as the index of the codeword in the state codebook which is the best match to the block

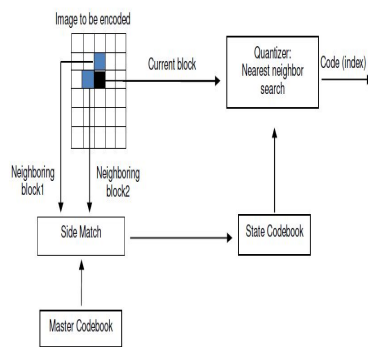


Fig 3. Block diagram of SMVQ encoder

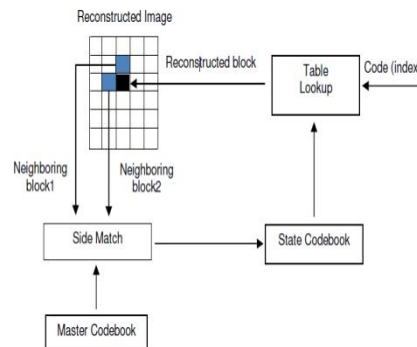


Fig 4. Block diagram of SMVQ decoder

- 2) **Decoding Process:** For the decoding of each image block, SMVQ first generates the state codebook which was used to encode it according to step (1) and (2) in the encoding process. Once the state codebook is generated, the reconstructed block is obtained by simply selecting the corresponding codeword in the state codebook using the index which is the code of the block generated in the encoding process. The block diagram of SMVQ decoder is shown in Figure.

C. Decompression

In the segmented section decompress the image according to the index values. The decompression for all blocks can also be achieved successfully by VQ, SMVQ, and image in painting.

D. Proposed System Algorithm

The algorithm of data hiding and image compression based on SMVQ include the following steps

- 1) Step1: Load input image size MN, M=Width of the image, N=Height of the image.
- 2) Step2: Evaluation of SMVQ Quality.
- 3) Step3: Compress using SMVQ and Image in painting Based on Index values.
- 4) Step4: Data extraction according to the index values with coding process.
- 5) Step5: Decompress using SMVQ and in painting

VI. EXPERIMENTAL RESULTS

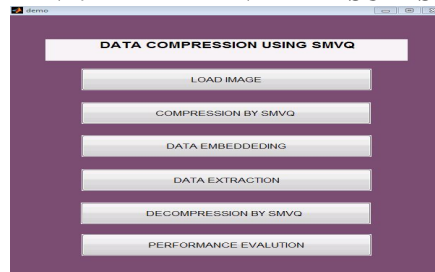


Fig.5. Display page

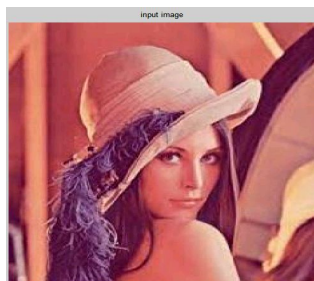


Fig. 6 Input Image

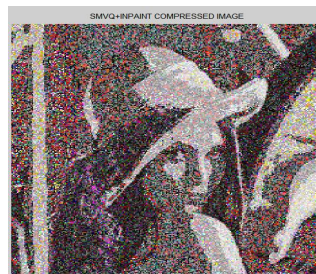


Fig.7 Compressed Image

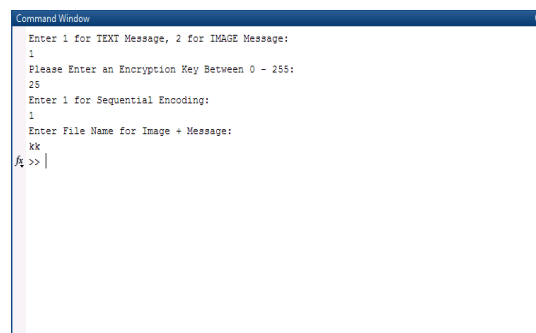


Fig.8 Entering Commands

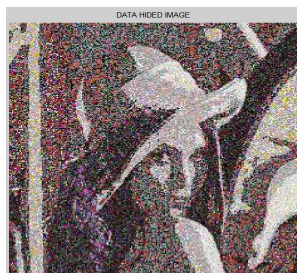


Fig.9 Hided Image

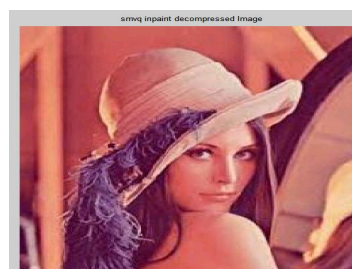


Fig.10 Decompressed Image


```

Command Window
originalImagePSNR =
    60.4383

ExtractedImagePSNR =
    36.7850

n =
    256

m =
    256

k =
    3

CR =
    7.8757
    
```

Fig.11 Final Results

VII. CONCLUSION

A hybrid technique for image compression is proposed in this paper and compared with two existing techniques. Different images are considered for experimentation. For all these four images we obtained the lesser value of RMSE, larger value for SNR, High compression percentage and high compression ratio for the proposed method. All these parameters showed the effective use of the hybrid algorithm over existing ones. Showed the improved RMSE and SNR values respectively for each image in case of proposed system.

REFERENCES

- [1] P. Seuntjens, L. Meesters, and W. Ijsselstein, "Perceived quality of compressed stereoscopic images: Effects of symmetric and asymmetric JPEG coding and camera separation," *ACM Trans. Appl. Percept.*, vol. 3, no. 2, pp.95-109, 2009.
- [2] M. G. Perkins, "Data compression of stereopairs," *IEEE Transactions on communications*, no. 40, pp. 684-696, 2009.
- [3] D. V. Meegan, L. B. Stelmach, and W. J. Tam, "Unequal weighting of monocular inputs in binocular combination: Implications for the compression of stereoscopic imagery," *Journal of Experimental Psychology: Applied*, vol. 7(2), pp. 143-153, 2012.
- [4] L. Stelmach, W. Tam, D. Meegan, A. Vincent, and P. Corriveau, "Human perception of mismatched stereoscopic 3D input," in *Image Processing, 2010. Proceedings. 2010 International Conference on*, vol. 1, 2010, pp. 5-8.
- [5] D. A. Leopold, J. C. Fitzgibbons, and N. K. Logothetis, "The role of attention in binocular rivalry as revealed through optokinetic nystagmus," Cambridge, MA, USA, Tech. Rep., 2011.
- [6] L. Kaufman, Ed., *Sight and Mind: An Introduction to Visual Perception*. University of Illinois Press, 2011.
- [7] G. M. Murch, "Review: [untitled]," *The American Journal of Psychology*, vol. 87, no. 4, pp. 742-746, 2000.
- [8] L. L. Kontsevich, "Pairwise comparison technique: a simple solution for depth reconstruction," *J. Opt. Soc. Am. A*, vol. 10, no. 6, pp. 1129-1135, 2003.
- [9] B. Julesz, "Foundations of cyclopean perception," 2002.
- [10] I. Dinstein, "Compression of stereo images and the evaluation of its effects on 3D perception," in *SPIE Applications of Digital Image Processing XII*, 1153, 522-30, 2010.
- [11] S. Sethuraman, M. Siegel, and A. Jordan, "A multiresolution framework for stereoscopic image sequence compression," in *Proc. ICIP-08*, vol. 2, November 2008, pp. 361 - 365.
- [12] I. Dinstein, G. Guy, J. Rabany, J. Tzelgov, and A. Henik, "On stereo image coding," in *In the International Conference on Pattern Recognition*, 2007, pp. 357-359.
- [13] L. Stelmach, W. J. Tam, D. Meegan, and A. Vincent, "Stereo image quality: effects of mixed spatio-temporal resolution," *Circuits and Systems for Video Technology, IEEE Transactions on*, vol. 10, no. 2, pp. 188-193, Mar 2010.
- [14] M. W. Siegel, P. Gunatilake, and S. Sethuraman, "Compression of stereo image pairs and streams," in *In Stereoscopic Displays and Applications V*, 2010, pp. 258-268.
- [15] M. Siegel, S. Sethuraman, J. S. McVeigh, and A. Jordan, "Compression and interpolation of 3D-Stereoscopic and multi-view video," in *Stereoscopic Displays and Virtual Reality Systems IV*, vol. 3012, February 2007, pp. 227 -238.
- [16] H. M. Al-Otun, "Qualitative and quantitative image quality assessment of vector quantization, JPEG, and JPEG2000 compressed images," *Journal of Electronic Imaging*, vol. 12, no. 3, pp. 511-521, 2008.
- [17] P. W. Gorley and N. S. Holliman, "Stereoscopic image quality metrics and compression," ser. *Stereoscopic Displays and Applications XIX*, SPIE Proceedings, vol. 6803, 2008.



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