IMAGE COMPRESSION USING WALSH-HADAMARD

A MINI PROJECT REPORT

submitted by

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towards partial fulfillment of the requirements for the award of the degree

of

Bachelor of Technology
in
Electronics & Communication Engineering

School of Electrical & Electronics Engineering

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NOVEMBER 2018

BONAFIDE CERTIFICATE

This is to certify that the project work entitled **"IMAGE COMPRESSION USING WALSH-HADAMARD"** is a bonafide record of the work carried out by

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Project Viva-Voice held on ______________________________

Examiner -I **Examiner-II**

ACKNOWLEDGEMENTS

First of all we express our gratitude to **PROF. R. SETHURAMAN**, Vice Chancellor, SASTRA University who provided all facilities & encouragement during the course of our study.We extend our sincere thanks to **Dr. G. Bhalachandran**, Registrar, SASTRA University for providing the opportunity to pursue this project.

We dedicate our whole hearted thanks to **Dr. K. Thenmozhi**, Associate Dean (ECE) and **Dr. R. John Bosco Balaguru**, Associate Dean (Research) who motivated us during the project work.

I heartily thank our project coordinators, **Dr. K Sridhar**, **Dr. R Ramesh** and **Dr. G Venkat Babu** for guiding us all along, till the completion of our project by providing all necessary information.

We owe a debt of deepest gratitude to our mentor **Dr. V. Padma Priya**, SAP, ECE, for her continuous support and guidance throughout the process viewing the pursuit of our project work. Her deep insight in the field and invaluable suggestions helped us in making progress through our project work.

We would like to dedicate this work with tremendous love to our **Parents** for their unlimited, ultra-supportive, encouragement, sacrifices and unconditional love throughout our entire life.

Above all, we thank the almighty for the divine grace we received throughout the research work, without which we could not have completed this work.

ABSTRACT

KEYWORDS: Walsh- Hadamard Transform, Saliency detection

Image processing software helps to automatically identify and analyze what might not be apparent to the human eye. The digitization and the development of communication systems depend critically on efficient compression algorithms. Thereby, to reduce transmission time and storage costs, efficient image compression schemes without degradation of image quality are needed.

Walsh-Hadamard Transform is orthogonal, a non-sinusoidal transform which is used in image filtering, compression, and medical signal analysis. This linear image transform is chosen because of their flexibility, energy compaction, and robustness. It effectively extracts the edges and also provides energy compaction. Saliency detection perceives the visual attention, the process of selecting particular information from the plenty of raw data perceived.

To demonstrate the efficient compression using Walsh - Hadamard Transform. Based on a review of the literature, this project introduces a simpler method to increase the transmission rate and effectively reduce the storage area.

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CHAPTER 1

INTRODUCTION

With the development of digital technology, it became important to preserve image data. Due to increase in demand on transfer and storage of data image compression become an important research area. Image compression aims at reducing the amount of data required to represent a digital image. It is a process that yields a compact representation of an image. It reduces the image storage/transmission requirements.

When the image size is reduced, it allows more images to be stored in a given amount of memory space. It also reduces the time required for images to be sent over the Internet. Image compression is one of the vast and highly explored area of research. Here, compression doesn't mean only reducing the image size. Along with reduction in data it also leads to the position to reconstruct the original data.[1]

In computer vision, images are one of the most important way to convey information. Some low contrast image can be enhanced by detecting object of interest and enhancing them. Brain can do this task very quickly but doing on a machine is a major challenge. The problem is closely related to many applications like object recognition and tracking, scene understanding, content-based image retrieval.

Segmentation could be used for image compression, image editing, object recognition, boundary estimation within motion or stereo systems. In this project, we provide an approach to detect all object in an image using entropy of an image[1]. The digitization and the development of picture achieving and communication systems (PACS) depend critically on efficient compression algorithms. Several image coding techniques have been developed for both lossy and lossless compression.

Image processing software helps to automatically identify and analyze what might not be apparent to the human eye, even of an expert. Computerized algorithms can provide temporal and spatial analysis to detect patterns and characteristics of the image[2]. Because of the transmission bandwidth constraints of transmission links, storage capacity limitations and high spatial resolution, the digital images need to be compressed selectively.

As growing of media communication and video on demand is desired, image data compression has received an increasing interest. The main purpose of image compression is to gain a very low bit rate and achieve a high visual quality of decompressed images. Image compression are used all fields of media communication such as multimedia, medical image recognition, digital image processing.

CHAPTER 2

REVIEW OF LITERATURE

2.1 DATA REDUNDANCY

Digital image compression is a field that studies the techniques for reducing the total number of bits required to represent an image. This can be achieved through the process of eliminating various types of redundancy that exist in the image. In general, there are three basic redundancies in digital images as follows [2]. □

2.1.1 Coding Redundancy: It assigns less number of bits for more frequent gray levels and more number of bits for less frequent gray levels, then the entire image can be represented by the least possible number of bits. By making use of some variable length code schemes such as Huffman coding and arithmetic coding, compression can be achieved. In this way, we can reduce the coding redundancy.

2.1.2 Inter-pixel Redundancy: It is a redundancy related to statistical dependencies among pixels, especially between neighboring pixels. Information is unnecessarily replicated in the correlated pixels.

2.1.3 Psycho-visual Redundancy: It is a redundancy corresponding to different sensitivities of human eyes to all image signals. Therefore, eliminating some less sensitive information from the image based on our visual processing.

2.2 TYPES OF IMAGE COMPRESSION

2.2.1 Lossless Compression:

In this compression technique, no data is lost. The exact replica of the original file can be retrieved by decrypting the encrypted file. Text compression is generally of lossless type. In this type of compression generally, the encrypted file is used for storing or transmitting data. For general purpose use, we need to decrypt the file.

2.2.2 Lossy Compression:

Lossy Compression is generally used for image, audio, video. In this compression technique, the compression process ignores some less important data and the exact replica of the original file can't be retrieved from the compressed file. To decompress the compressed data we can get a closer approximation of the original file.[2]

2.3 LOSSLESS COMPRESSION TECHNIQUES

In this section, we will give a short review and explanation for each one of the lossless compression methods.

2.3.1 Huffman Encoding:

It uses variable length code for encoding a source symbol which is derived based on the estimated probability of occurrence for each possible value of the source symbol. In this compression technique, a table is created incorporating the no of occurrences of an individual symbol. This table is known as a frequency table and is arranged in a certain order. Then a tree is generated from that table, in this tree high-frequency symbols are assigned codes which have fewer bits, and less frequent symbols are assigned codes with many bits.

2.3.2 Run Length Encoding:

Run-length coding (RLC) works by counting adjacent pixels with the same gray level value called the run-length, which is then encoded and stored [3]. RLC works best for binary, two-valued, images. RLE requires only a small amount of hardware and software resources. Run-length encoding is a data compression algorithm that is supported by most bitmap file formats, such as TIFF, BMP, and PCX[4].

2.3.3 Arithmetic Encoding:

Arithmetic coding transforms input data into a single floating point number between 0 and 1. -There is not a direct correspondence between the code and the individual pixel values. Arithmetic coding uses the probability distribution of the data (histogram), so it can theoretically achieve the maximum compression specified by the entropy. It works by successively subdividing the interval between 0 and 1, based on the placement of the current pixel value in the probability distribution.

2.4 LOSSY COMPRESSION TECHNIQUES

Transform coding:

Transform coding is a type of data compression for natural data like audio signals or images. This technique is typically lossy, resulting in a lower quality copy of the original input. In transform coding, knowledge of the application is used to choose information to discard, thereby lowering its bandwidth. The remaining information can be compressed via a number of methods when the output is decoded, the result may not be identical to the original input, but is expected to be close enough for the purpose of the application.[5]

2.4.1 Discrete Cosine Transform (DCT):

A discrete expresses a finite sequence of data points in the terms of the sum of cosine functions oscillating at different frequencies. DCT is a lossy compression technique which is widely used in the area of image and audio compression. DCTs are used to convert data in the summation of series of cosine waves oscillating at different frequencies. There are very similar to Fourier transforms but DCT involves uses of cosine functions are much more efficient as fewer function are needed to approximate a signal. [6]

2.4.2 Discrete Wavelet Transform(DWT):

The DWT is an implementation of the wavelet transform using a discrete set of the values scales and translations obeying some defined rules. In other words, this transform decomposes the signal into a mutually orthogonal set of wavelets which is the main differences from the continuous wavelet transform or its implementation from the discrete time series sometimes called Discrete –time continuous wavelet transform (DTCWT). DWT is applied to the image block generated by the pre-processor.[6]

2.4.3 Walsh Hadamard Transform(WHT):

WHT is perhaps the most well-known of the nonsinusoidal orthogonal transforms. The WHT has gained prominence in various digital signal processing applications, since it can essentially be computed using additions and subtractions only. Consequently its hardware implementation is also simpler.The transformation has no multipliers and is real because the amplitude of Walsh functions has only two values, +1 or -1.Therefore WHT can be used in many different applications, such as power spectrum analysis, filtering, processing speech and medical signals, multiplexing and coding in communications, characterizing non-linear signals, solving non-linear differential equations, and logical design and analysis.

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CHAPTER 3

SCOPE OF THE PRESENT WORK

Image compression has increased the efficiency of sharing and viewing personal images, it offers the same benefits to just about every industry in existence. Image compression was most commonly used in the data storage, printing and telecommunication industry. The digital form of image compression is also being put to work in industries such as fax transmission, satellite remote sensing, and high definition television [4][6].

In certain industries, the archiving of large numbers of images is required. A good example is the health industry, where the constant scanning and/or storage of medical images and documents take place. Image compression offers many benefits here, as information can be stored without placing large loads on system servers. Depending on the type of compression applied, images can be compressed to save storage space, or to send to multiple physicians for examination. And conveniently, these images can uncompress when they are ready to be viewed, retaining the original high quality and detail that medical imagery demands [5] [6].

In the security industry, image compression can greatly increase the efficiency of recording, processing and storage. However, in this application it is imperative to determine whether one compression standard will benefit all areas. For example, in a video networking or closed-circuit television application, several images at different frame rates may be required. Time is also a consideration, as different areas may need to be recorded for various lengths of time. Image resolution and quality also become considerations, as does network bandwidth, and the overall security of the system [4] [6].

CHAPTER 4
EXPERIMENTAL PROCEDURES

4.1 INTRODUCTION:

Figure 4.1 shows the framework of the saliency-based image compression. It involves two phases. The first phase is the saliency map computation based on WHT and entropy. The second phase consists of WHT-based image compression. Saliency-based detection yields better results by reducing the correlation between the pixels. Thereby, we can easily identify the redundant information. The quantization block is used to reduce the number of bits needed for the transformed coefficients. Entropy coding is used in the encoder block in order to get the compressed image.

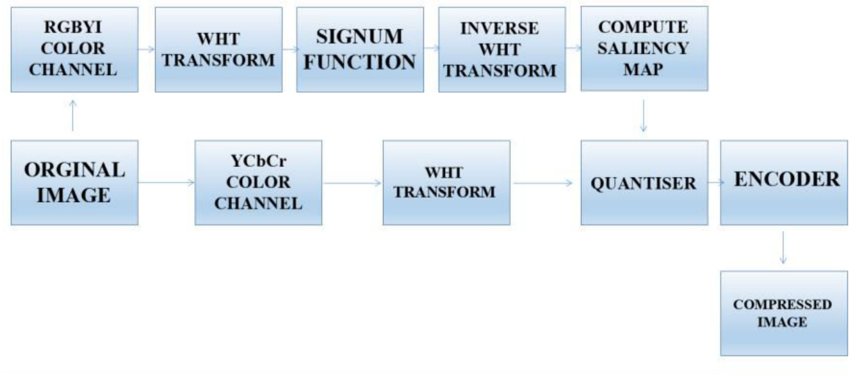

Fig 4.1 Detailed flow of image compression

4.2 RGBYI COLOR CHANNELS

Basically, image features include color, orientation, texture, and shape. In order to identify the salient regions, the suitable color channels must be used. RGB is one of the highly correlated color spaces, whereas lab color space is a well-decorrelated color space with uniformity [7].

Recently, RGBYI color channels are used in saliency detection [8]. In this method, RGB color channel is employed because this color channel mimics the visual cortex of human system by involving color channel pairs such as yellow/blue, blue/yellow, red/green, and green/red. It also includes color difference channels and four broadly tuned color channels.

Let r, g, and b be the red, green, and blue color channels of an input image.

$$\text{Intensity} = \frac{r+g+b}{3} \tag{4.1}$$

$$\text{RE} = r - \frac{g+b}{2} \tag{4.2}$$

$$\text{GR} = g - \frac{r+b}{2} \tag{4.3}$$

$$\text{BL} = b - \frac{r+g}{2} \tag{4.4}$$

$$\text{REGR} = R - G \tag{4.5}$$

$$\text{BLYE} = B - Y \tag{4.6}$$

$$\text{YELLOW} = \frac{r+g}{2} - \frac{|r-g|}{2} - b \tag{4.7}$$

These equations represent RE, GR, BL, REGR, BLYE, INTENSITY color channels derived from red, blue and greeen channels.

Fig 4.2 RGBYI Color Channels

4.3 WALSH HADAMARD TRANSFORM

$$H(u,v) = (1/N)\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(x,y)\,(-1)^{\sum_{i=0}^{n-1}[b_i(x)b_i(u) + b_i(y)b_i(v)]} \tag{4.8}$$

WHT is used in saliency detection as well as image compression. WHT is chosen because the number of computations in this transform is significantly less compared to the other transforms, and WHT is the key transform to provide energy compactness. Finding the salient information in image/audio/video will reduce the number of computations and lesser hardware in the compression techniques.

The Walsh–Hadamard transform (WHT) has lesser computations and extremely fast transform. It is computed only by addition and subtraction. Lesser hardware is required for practical implementation [9]. The highly correlated pixels are captured by the WHT in the visual space. It performs an orthogonal, symmetric, involutive, linear operation on 2m real numbers. The transformation has no multipliers and is real because the amplitude of Walsh (or Hadamard) functions has only two values, +1 or -1.

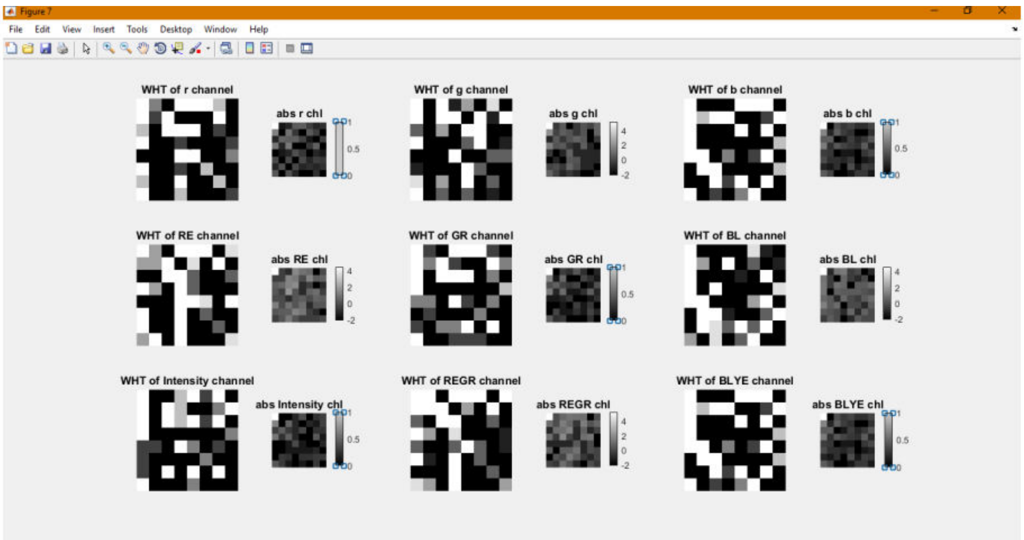

Fig 4.3 WHT of RGBYI Color Channels

4.4 SIGNUM FUNCTION

In Eq 4.9, Sign (.) represents signum function. Let consider I^C be the color image. Each channels of IC are applied with Walsh– Hadamard transform, and the transformed image is represented as

$$X = \text{sign}\ (\text{WHT}\ I^C) \tag{4.9}$$

Signum function is an odd mathematical function that extracts the sign of a real number. In mathematical expressions, the sign function is often represented as sgn. It holds only sign information of WHT components, that is only binary information (1 and -1). It is very compact since single bit representation is used for each component. Thereby, it reduces highly correlated features.

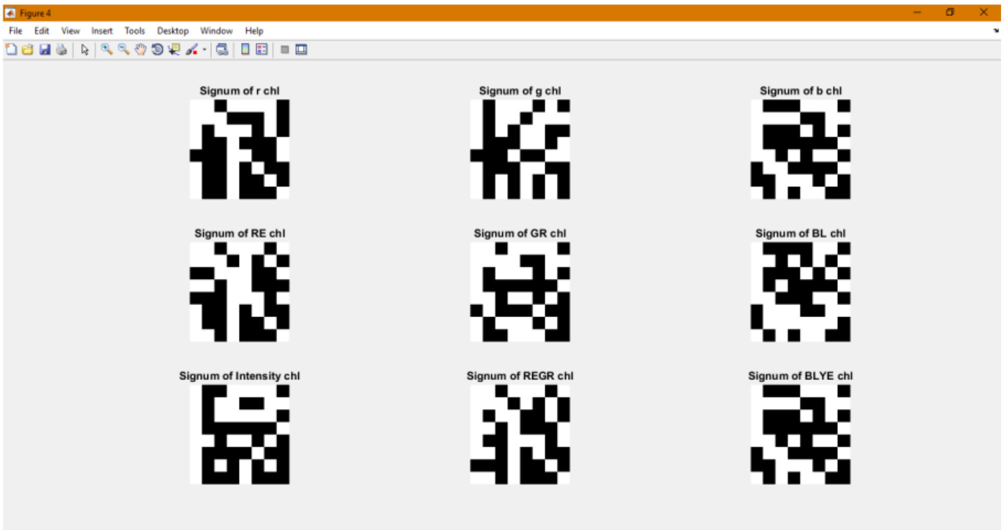

Fig 4.4 Signum of RGBYI Color Channels

4.5 INVERSE WALSH HADAMARD TRANSFORM

$$Y = \text{abs}(\text{IWHT}(X)) \tag{4.10}$$

The inverse Walsh-Hadamard transform operates only on signals with length equal to a power of 2. If the length of x is less than a power of 2, its length is padded with zeros to the next greater power of two before processing. Inverse

2D-Walsh-Hadamard Transforms do not use memory for the transposition operation. The results show that it has a very high throughput which makes them very suitable for several images, video processing applications and embedded systems. IWHT is implemented using 2-input adder and subtractor blocks.

Fig 4.5 IWHT of RGBYI Color Channels

4.6 SALIENCY MAP

Humans has the tendency to perceive visual information that is getting in through their eyes. Visual attention is the process of selecting particular information from huge amount of raw data.

For example, while sincerely watching a cricket match in the play ground, a sudden change in the action of the umpire picks the attention of the spectators in the gallery despite of the actions of batsmen, bowlers, and fielders is there. The eyes of the spectators gaze the umpire momentarily before shifting to other events in the visual scene. The phenomenon of drawing the focus of attention to certain regions in a given scene or image is called visual attention [6]. In the jargon of computer vision, these regions are known as salient regions.

$$\text{SMAP} = \sum_{i=1}^{9} \frac{Y_i}{M\{H(Y_i)\}} \tag{4.11}$$

In Equation 4.11, 'M' is for the normalization operator [0 1], where H (.) is the entropy. It is defined as

$$H(y) = -\sum_{i=1}^{n} p_i \log p_i \tag{4.12}$$

In equation 4.12, pi is the probability of different values of y. It varies from 0 to 255. 'n' is the possible values of 'y'. If the saliency map is having higher entropy, then the weight will be a lower one. The weight of the saliency map and its entropy are inversely proportional to each other. To smooth the saliency map, the Gaussian low-pass filter is applied before the updation of entropy.

4.7 YCbCr COLOR CHANNELS

It is a highly decorrelated color space. Human visual system is more sensitive to luminance rather than chrominance. Here Y describes how bright the pixel is. Cb & Cr tells actual color of the pixel & this is downsampled to lower resolution.

Figure 4.6 shows the Y, Cb and Cr color channels. These are obtained using rgb2ycbcr(image).

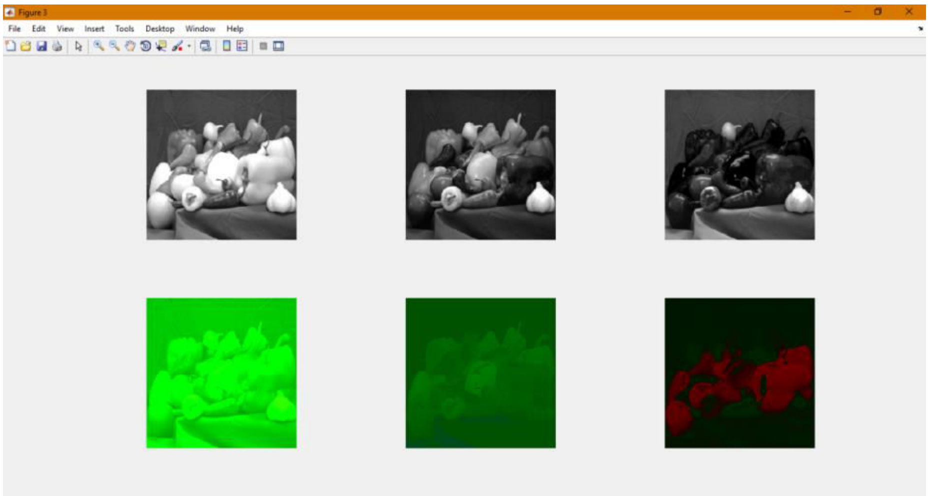

Fig 4.6 YCbCr Color channels

4.8 QUANTISATION

Quantization is a lossy compression technique achieved by compressing a range of values to a single quantum value. When the number of discrete symbols in a given stream is reduced, the stream becomes more compressible. The main advantage is that it increases performance and reduces the correlation between two adjacent pixels.

$$\mathrm{SMAP}'(x,y) = \begin{cases} 0, & \text{if } x \le 0.08 \text{ and } y \le 0.08 \\ 1, & \text{otherwise} \end{cases} \tag{4.13}$$

In Eq 4.13, x denotes the rows and y denotes the columns of the SMAP’ matrix. Visual saliency-based modified Hadamard matrix is obtained by multiplying the WHT coefficients with the human visual saliency map.

$$H'(x,y) = H(x,y) * \mathrm{SMAP}'(x,y) \tag{4.14}$$

Now, the quantitation matrix contributes the perceptual quality of human attention. The quantization matrix can be obtained by equation 4.15

$$Q(x,y) = \frac{q}{H'(x,y)} \tag{4.15}$$

In Equation 4.16, rounding operation of quantisation matrix is performed.

$$Q'(x, y) = \text{round}[Q(x, y)] \tag{4.16}$$

4.9 ENCODER

Huffman encoding is used as variable length code for encoding a source symbol which is derived based on the estimated probability of occurrence for each possible value of the source symbol. In this compression technique, a table is created incorporating the no of occurrences of an individual symbol. This table is known as a frequency table and is arranged in a certain order. Then a tree is generated from that table, in this tree high-frequency symbols are assigned codes which have fewer bits, and less frequent symbols are assigned codes with many bits.

CHAPTER 5

RESULTS AND DISCUSSION

5.1 COMPRESSION RATIO (CR)

It is defined as the ratio between the Original Image and the Compressed Image.

$$C_R = \frac{n_1}{n_2} \tag{4.17}$$

In equation 4.17, n1 denotes the number of bits in original image and n2 denotes the number of bits in compressed image.

5.2 MEAN SQUARE ERROR (MSE)

Equation 4.18 represents the cumulative squared error between the compressed and the original image.

$$MSE = \frac{\sum_{M,N} [I_1(m,n) - I_2(m,n)]^2}{M * N} \tag{4.18}$$

where M and N are the number of rows and columns, I1 represents original image & I2 represents compressed image.

5.3 PEAK SIGNAL TO NOISE RATIO (PSNR)

$$PSNR = 10 \log_{10}\left(\frac{R^2}{MSE}\right) \tag{4.19}$$

Equation 4.19 represents a measure of the peak error. If it has an 8-bit unsigned integer data type, R is 255 and MSE is defined in equation 4.18.

5.4 STRUCTURAL CONTENT (SC)

Equation 4.20 measures the information content of the image. It is the ratio of the structural information content of the original to the recovered information content. A large value means that the image is poor quality.

$$\mathrm{SC} = \frac{\sum_{m=1}^{M} \sum_{n=1}^{N} \mathrm{x(m,n)}^2}{\sum_{m=1}^{M} \sum_{n=1}^{N} x^\wedge(\mathrm{m,n})^2} \tag{4.20}$$

Here x(m,n) represents original image and x^(m,n) represents compressed image.

5.5 NORMALIZED CROSS CORRELATION (NCC)

Simplest and effective method as a similarity measurement.

Defined as

$$\mathrm{NCC} = \frac{\sum_X \sum_Y w(x,y) w'(x,y)}{\sum_X \sum_y [w(x,y)]^2} \tag{4.21}$$

In equation 4.21, w(x,y) represents original image and w’(m,n) represents compressed image.

5.6 AVERAGE DIFFERENCE (AD)

AD is simply the average of difference between the reference image and compressed image.

$$AD = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (x(i,j) - y(i,j)) \tag{4.22}$$

In equation 4.22, M and N are the number of rows and columns, x(i,j) represents original image & y(i,j) represents compressed image.

5.7 MAXIMUM DIFFERENCE (MD)

MD is the maximum of the error signal (difference between the reference image and Compressed image).

$$MD = MAX\left|x(i,j) - y(i,j)\right| \tag{4.23}$$

In equation 4.23, x(i,j) represents original image & y(i,j) represents compressed image.

5.8 NORMALIZED ABSOLUTE ERROR(NAE)

$$NAE = \frac{\sum_{m=1}^{M}\sum_{n=1}^{N} |O(m,n) - N(m,n)|}{\sum_{m=1}^{M}\sum_{n=1}^{N} |O(m,n)|} \tag{4.24}$$

In Equation 4.24, O(m,n) represents original image & N(m,n) represents compressed image.

5.9 TABULATION OF THE RESULTS

Image quality metrics are computed mainly for optimization purpose where one maximizes quality at a given cost, provides comparative analysis between different alternatives and applying in real time. The quality of image is influenced by many factors and is difficult to express in single numerical metric.

Here, image quality metrics for five different images have been computed and results were tabulated.

IMAGES / PARAMETERS	IMAGE 1	IMAGE 2	IMAGE 3	IMAGE 4	IMAGE 5
COMPRESSION RATIO	438.86	400.758	395.258	200.8	454
MEAN SQUARE ERROR	9.011e+03	1.222e+04	2.744e+04	2.51e+04	1.16e+04
PEAK SIGNAL TO NOISE RATIO	8.58	7.257	3.746	3.55	7.46
STRUCTURAL CONTENT	28.598	39.334	89.174	49.478	22.525
NORMALISED CROSS CORRELATION	0.006	0.009	0.007	0.009	0.011
AVERAGE DIFFERENCE	80.45	99.494	159.336	151.9	89.9
MAXIMUM DIFFERENCE	255	206	244	254	255
NORMALISED ABSOLUTE ERROR	1.008	1.003	0.998	1.001	1.01

CHAPTER 6

CONCLUSIONS

In this Project we applied Walsh Hadamard Transform for image compression. Here, we implemented Visual Saliency based image detection for obtaining efficient compression. Saliency detection perceives the visual attention, the process of selecting particular information from the plenty of raw data perceived.

Walsh-Hadamard Transform is orthogonal, a non-sinusoidal transform which is used in image filtering, compression, and medical signal analysis. This linear image transform is chosen because of their flexibility, energy compaction, and robustness. It effectively extracts the edges and also provides energy compaction.

From the tabulation of results, our project shows that image1 has high PSNR compared to other images. Thus, it concludes that image1 has better quality and less error introduced. Compression ratio is higher and mean square error is lower for image 5. Structural content is higher for image 3, which indicates that greater image similarity with good accuracy and consistency. Experimental results indicate that image 1 has moderate value for all quality metrics and hence leads to better compression.

Simulation results of the proposed image compression and comparisons to recent peer transforms indicate that the proposed image compression outperforms or atleast reaches state-of-the-art suggested by these peer tranforms with respect to a number of evaluation and analysis methods.

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