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Optimizing Fast Fourier Transform (FFT) Image Compression using Intelligent Water Drop (IWD) Algorithm

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Abstract

Digital image compression is the technique in digital image processing where special attention is provided in decreasing the number of bits required to represent a digital image. A wide range of techniques have been developed over the years, and novel approaches continue to emerge. This paper proposes a new technique for optimizing image compression using Fast Fourier Transform (FFT) and Intelligent Water Drop (IWD) algorithm. IWD-based FFT Compression is a emerging methodology, and we expect compression findings to be much better than the methods currently being applied in the domain. This work aims to enhance the degree of compression of the image while maintaining the features that contribute most. It optimizes the FFT threshold values using swarm-based optimization technique (IWD) and compares the results in terms of Structural Similarity Index Measure (SSIM). The criterion of structural similarity of image quality is based on the premise that the human visual system is highly adapted to obtain structural information from the scene, so a measure of structural similarity provides a reasonable estimate of the perceived image quality.

Keywords

Structural Similarity Index, Fast Fourier Transform, Intelligent Water Drop, Image Compression.

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I. Introduction

The application of images is expanding very rapidly. It is indispensable in the fields of remote sensing [1], video processing [2], medical science [3], machine/robot vision [4], and many other applications. Considering the rapid growth in the application scope of images, there is an increased demand for mass information storage and fast communication links [5].

Image compression applications use multiple methods and algorithms for compressing images, such as JPEG2000 [6], EBCOT [10], 2-D wavelet transformation [11]. The methods thus used can be categorized as lossless and lossy compression for image compression applications.

The compression method employed depends on the quality of the necessary output. If the application for image compression is expected to produce a very high-quality output without any loss of fidelity, then the lossless compression method is used. The lossy compression [12] method is used in applications where some quality can be compromised. There is a slight loss of quality in lossy compression, but the loss is too small to be noticed in terms of structural resemblance (SSIM) index and visual resemblance [19]–[21].

The digital image processing [7]–[9] techniques such as image sharpening and restoration, transmission and encoding, pattern recognition are optimized by maximizing the compression rate while maintaining an optimum percentage of data required to reconstruct the image with the highest quality [13]. The proposed optimized approach ensures quality along with efficient memory utilization. The proposed system aims to produce a compact image representation by reducing the requirements for image storage transmission, and processing. Malathkar et.al proposed an image compression algorithm consisting of a new simplified YUV colour space, corner clipping, uniform quantization, subsampling, differential pulse code modulation and Golomb Rice code for wireless capsule endoscopy [22]. In [23], the authors evaluate various compression models on their complexity and efficiency using various E-Learning images (Colour and Grey Scale) with different compression quality measurements.

Traditional image compression methods compress an image to such an extent that the decompressed image has much less structural similarity (SSIM) index [14] to the original one. The

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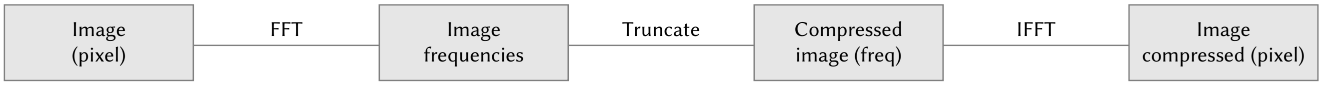


Fig. 1. Block diagram for image compression using Fast Fourier Transform.

procedure as visualised in Fig. 1, typically starts with applying Fast Fourier Transform(FFT) to the image and truncating the frequency domain output with specified threshold (independant of image content) followed by applying an inverse FFT to generate the compressed image. The proposed system uses fast fourier transform (FFT) [15] with optimized threshold values for each colour channel to compress the image that the decompressed image obtains high structural similarity (SSIM) index, thus extracting the contributing characteristics of the image.

A. Motivation

This section addresses the two factors that motivate the research undertaken in this study. First, there is plenty of research on optimizing compression techniques, but none have discussed concurrently compressing an image to its maximum level while sustaining its best possible quality. Second, there is a need to enhance the storage and transmission of compressed images. At times the storage and transmission costs are very high, to reduce the cost and fulfil the requirements of targeted process combination of optimum compression rate and quality must be achieved.

This paper is organized as follows. Section II explains the intelligent water drop (IWD) algorithm. Section III describes the image compression using fast Fourier transform (FFT). Section IV explains about structural similarity index (SSIM). Section V shows the proposed system. Section VI explains experimental results obtained using several sample images. Section VII concludes the complete research.

II. Intelligent Water Drop Algorithm

The algorithm Intelligent Water Drop (IWD) is motivated by studying the actual behaviour of natural drops in a flowing water source from elevated altitude to low altitude areas. A massive collection of drops governs water flow, each moving based on a shorter and simpler path naturally influenced, although subject to several environmental constraints. Shah-Hosseini expanded this basic idea to introduce the Intelligent Water Drop (IWD) algorithm for Traveling Salesman Problem (TSP) [16].

An IWD consists of two significant properties, similar to a natural water drop. These are a) the $IWD{-}soil(IWD)$ soil content and b) the $IWD{-}vel(IWD)$ velocity. The IWD's soil and velocity content dynamically change depending on the same route as it flows through the problem's discrete landscape. Therefore, depending on the movement of the IWD, some soil is removed from the traversed path and the corresponding soil path is dynamically updated in the process. Such flow leads to soil content decrease in ideal paths depending on the problem's setting. Thus it can be said that the routes with reduced soil content may be the most relevant to finding an almost ideal solution. Thus, the building of an ideal solution to the issue is governed by a set of evolving swarm behaviour linked to IWDs.

Concerning the original formulation of TSP problems, we can consider a graph $G = (V, E)$ where V is the set of nodes and E is the set of edges. Thus an IWD can be randomly positioned at any node. Say i, it follows the transition of probability as given in equation (1) to select the next node j.

$$P(i,j) = \frac{f(soil(i,j))}{\sum_{k \notin vc(IWD)} f\,(soil(i,k))} \tag{1}$$

$$f(soil(i,j)) = \frac{1}{\epsilon + g(soil(i,j))} \tag{2}$$

$$g(soil(i,j)) = soil(i,j) \;\; if \;\; minsoil \geq 0 \tag{3}$$

$$soil(i,j) - minsoil \quad if \quad minsoil < 0 \tag{4}$$

P(i, j) shows the transition probability of node j. K denotes exactly all nodes to be visited and π is the parameter of the algorithm. Thus, a node selection depends on the quantity of soil present on the edges among adjacent nodes given by soil(i,j) in a probabilistic way. Here min soil shows the least amount of soil on a path between any node i and j. The state transition probability of an IWD, as illustrated in equations (1) to (3), is therefore proportional to the soil content available in the edge between nodes i and j. As a result, as a path's soil content decreases, the probability of selecting the appropriate component of the solution increases. While each IWD moves incrementally from one node I to j while building a solution, the soil content of the IWD (soil(iwd)) and the velocity of the same (level(iwd)) is also updated based on equations (5-7).

$$\Delta vel^{IWD}(t) = \frac{a_v}{b_v + c_v \times soil^{2\alpha}(i,j)} \tag{5}$$

$$\Delta soil(i,j) = \frac{a_s}{b_s + c_s \times times^{2\beta}(i,j)} \tag{6}$$

$$time(i,j) = \frac{HUD(i,j)}{vel(IWD)} \tag{7}$$

HUD is a heuristic that can be used to measure an IWD's desirability/unwantedness to select an edge between *i* and *j*, in this case. Therefore, a higher IWD velocity helps minimize the time an IWD takes to move from *i* to *j*. In turn, the time factor influences the amount of soil from a path to be removed (as shown in equation 5). The soil content of the entire solution path can be updated based on Equation (8) once the IWD attributes are calculated.

$$soil(i,j) = \rho_0 \times soil(i,j) - \rho_n \times \Delta soil(i,j) \tag{8}$$

Where ρ_0 and ρ_n remain within 0 and 1, according to the original TSP IWD algorithm, $\rho_0 = 1 - \rho_n$.

III. Fast Fourier Transform (FFT) for Image Compression

The Fourier transformation (FT) decomposes a time (a signal) into its constituent frequencies (also called analysis). This is similar to how a musical can be expressed in terms of its constituent notes volumes and frequencies (or pitches). The term Fourier transform refers to a function of time, both the representation and the mathematical operation associating the representation of the frequency domain.

A fast Fourier transformation (FFT) is an algorithm calculating the discrete Fourier transformation (DFT) or its inverse(IDFT) of a sequence. Analysis of Fourier converts a signal from its original domain in the frequency domain (often time or space) and vice versa. The DFT is obtained by breaking down a sequence of values into different components of the frequency.

Consider the pixel space image and apply a Fast Fourier Transform (FFT) to get a frequency domain image . For RGB layers, threshold values are calculated by truncating values below the calculated threshold, resulting in a compressed image in the frequency domain.

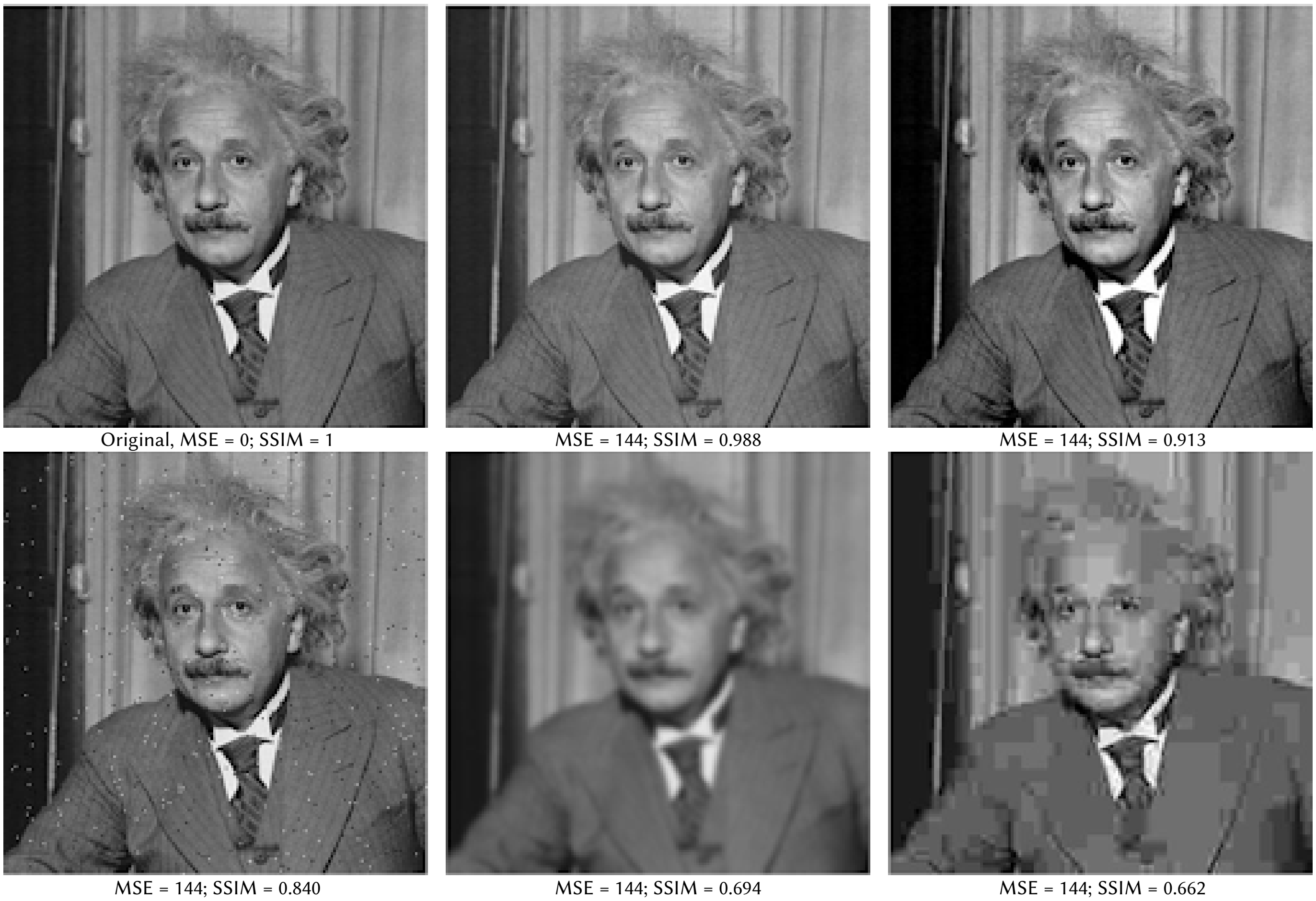


Fig. 2. Mean Squared Error (MSE) vs Structural Similarity Index Measure (SSIM).

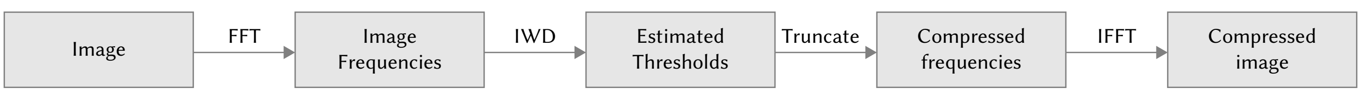


Fig. 3. Block diagram for image compression using Fast Fourier Transform (FFT) and Intelligent Water Drop Algorithm (IWD).

To obtain the compressed image in pixels, the Inverse Fourier Transform is carried out.

IV. Structural Similarity (SSIM) Index

The Structural Similarity (SSIM) index is a method employed to estimate the similarity in two images [18]. The SSIM index is studied as a measure of the quality of one of the images being examined, provided that the other image is considered to be of perfect quality. It is an enhanced version of the previously proposed universal image quality index.

For the examples shown in Fig. 2, all distorted images have about the same mean squared error (MSE) values for the initial image, but very distinct performance. SSIM offers a much better indication of image quality.

V. Our Proposed Solution

Using Fast Fourier Transforms, the compression of images involves thresholding the complex Fourier coefficients and applying reverse Fourier transform to the result in order to restore the image. These thresholds should be carefully chosen because the image can not be compressed by too low threshold while too high can result in very lossful compression. These thresholds are previously selected experimentally and are hard-coded for all images. Our experiments show that each compressed image tends to have its own set of thresholds, resulting in a better compression as well as a better quality ratio. But running the compression algorithm significantly for each image with different parameters is a very heavy and computationally expensive task to find an optimal solution. Also, the thresholds for RGB images are a triplet of 3 values instead of 1 value. Consequently, the complexity of such a task increases even more in the case of RGB images. There are some approximations available that can be used to estimate a set of threshold values, but none of them work well in terms of space or time complexity to our extent of knowledge.

For which, we suggest the intelligent water drops algorithm (IWD) to estimate these triplet's values. The task in hand is to estimate 3 discrete threshold values for each image compression. But producing these values directly may not be an optimal way to get the result. Instead, we try to obtain parameter (p1, p2, p3) for these 3 discrete values that are multiplied by the maximum absolute value of the RGB channel yield threshold of the complex fourier coefficients.

IWD optimizes several problem areas, such as n-queens, traveling salesman, multiple knapsack, but here we used IWD's traveling salesman variant to fulfill our task of finding the optimal three parameters as shown in Fig. 3.

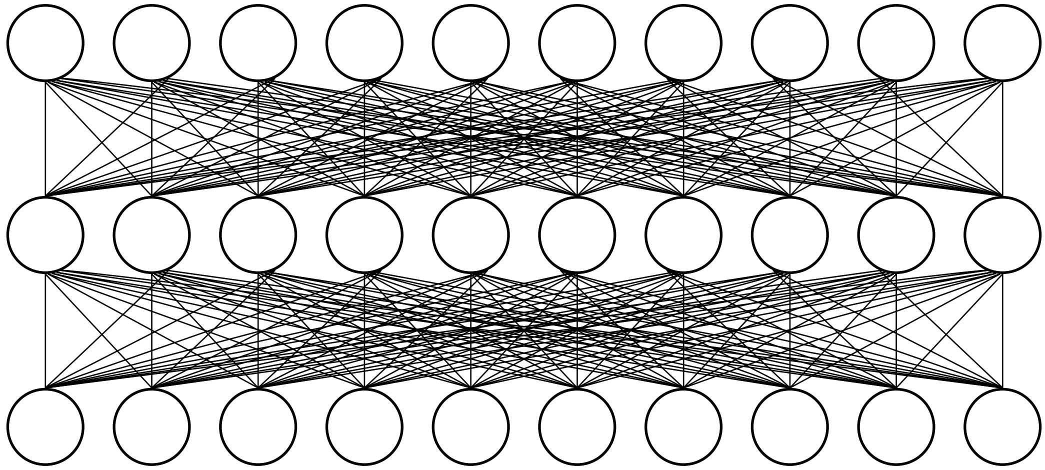


Fig. 4. Each layer has 10 nodes of values from 0.001 to 0.01 with step size of 0.001, where each node is connected to each other in the next layer. Layers 1, 2 and 3 may have p1, p2 and p3 values respectively. The IWD starts at layer 1 with any node and stops at layer 3 when it reaches a node.

(a) (b) (c) (d)

Fig. 5. (a) Sample image 1, (b) Sample image 2, (c) Sample image 3, (d) Sample image 4.

A. Modeling of the Problem

Our experiments with different threshold sets show that the value to be optimized for these parameters tends to lie in a limited region of parameter space, i.e. 0.001-0.01. We have modelled a graph of 30 nodes, 10 nodes for each of the 3 threshold triplet values by incorporating this prior knowledge about the parameter space. The value of each of the 10 nodes is 0.001 higher than the previous node (see Fig. 4). From these 10 discrete values, IWD is then used to find the best triplet combination that increases the image's SSIM along with the highest compression ratio.

The IWD algorithm computes the Local Heuristic H(j) for every node it moves forward to (j is the next node of the graph where the drop will move), for our task, we have used a constant heuristic 1.

Algorithm

- function quality:

1. input : values of $p1$, $p2$, $p3$
2. Calculate the maximum absolute value (say max_{val}) from fourier coefficients.
3. Calculate thresholds by multiplying the maximum absolute value with $p1$, $p2$ and $p3$.
4. $Thresholds = (p1 * max_{val}, p2 * max_{val}, p3 * max_{val})$
5. Filter the fourier coefficients by zeroing out those which are less than the calculated threshold.
6. Apply inverse fourier transform to the filtered coefficients to obtain decompressed image.
7. Calculate SSIM score using decompressed and original image.
8. return SSIM

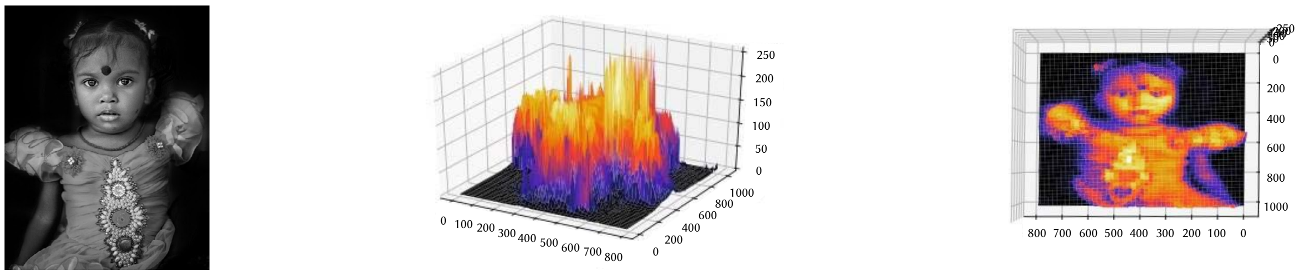
It is necessary to rank each solution produced by an IWD based on its quality. For each iteration, for each droplet and for the best global solution, IWD calculates this quality. We used a quality function for our task that takes the traveled path (in our case the p1, p2 and p3 values) and compresses the image using these thresholds and returns the SSIM score of that particular compression.

VI. Experimental Results

In simulations, to compare the results obtained from the traditional method and the IWD-based FFT compression method four sample images were selected. These images were directly scraped from the internet with query, "high fidelity images", "high resolution colored images" and "HD portraits". Fig. 5 shows the four sample images selected for experimental results.

Fig. 6, 8, 10 and 12 represent the grayscale, surface plot and top view plot of sample image 1, 2, 3 and 4 respectively. In the grayscale image, where the threshold is a single value, as applied in the image in Fig. 7, the visual quality of the image is preserved even after suppressing 98.17 per cent of the data in an image. Similarly in Fig. 9, Fig. 11, Fig. 13 the visual quality of the image is preserved even after the image is highly compressed. In the case of RGB images, the threshold is separate for each channel, thus the same procedure of hit and trial can be implemented for each channel separately.

It is concluded from Fig. 7, Fig. 9, Fig. 11, Fig. 13 that as more amount of data is suppressed, the less visually similar the images look. The quality of an image and the amount of compression is a tradeoff between each other. Hence, the threshold for compression must be chosen carefully, such that, the quality of the image along with compression maximizes. Every image has its own set of features along the channels that must be taken in order to achieve maximum quality.



(a) (b) (c)

Fig. 6. (a) represents the grayscale of sample image 1, (b) represents surface plot, and (c) represents top view plot.

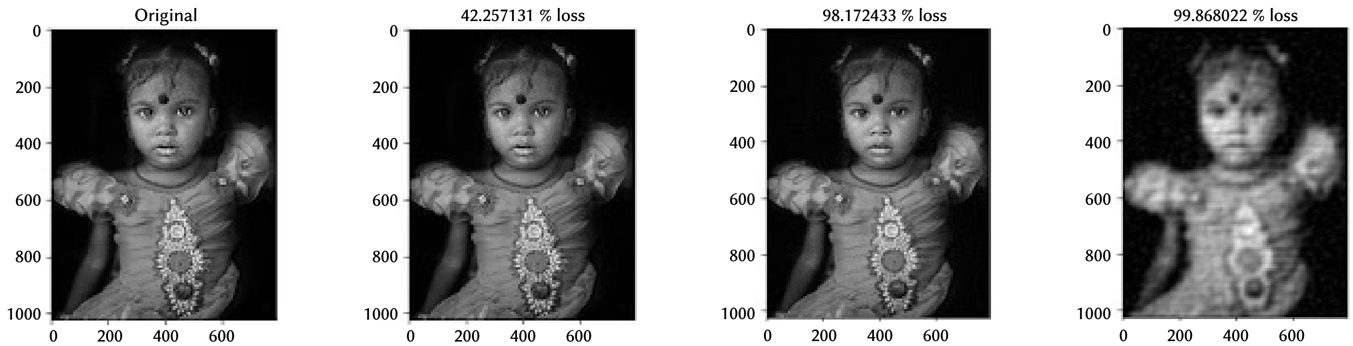
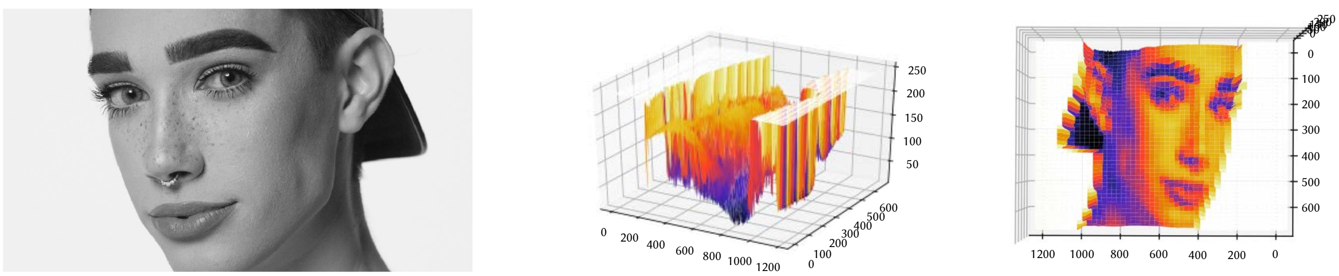


Fig. 7. Representations of the results of compression using Fourier transforms with the selected thresholds.



(a) (b) (c)

Fig. 8. (a) represents the grayscale of sample image 2, (b) represents surface plot, and (c) represents top view plot.

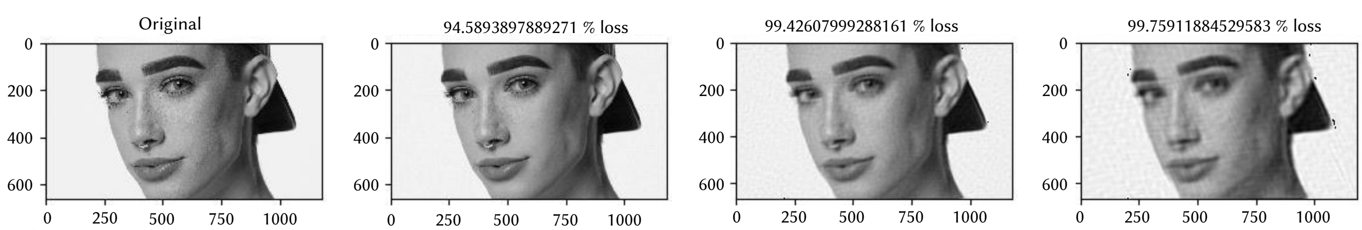
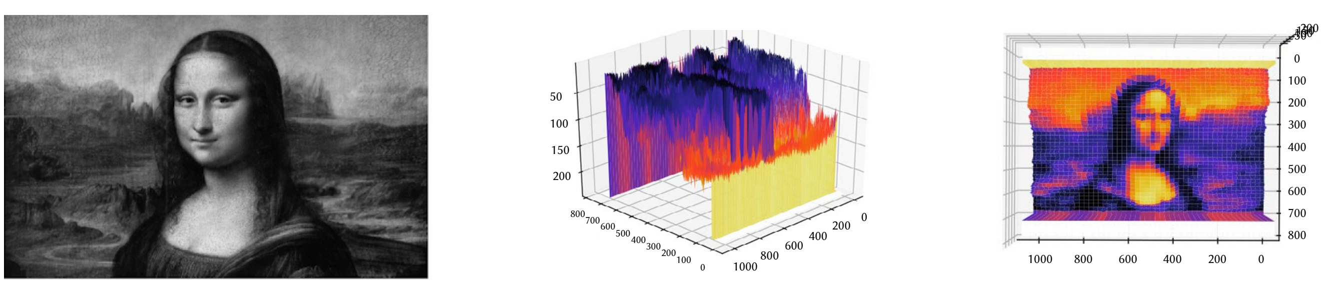


Fig. 9. Representations of the results of compression using Fourier transforms with the selected thresholds.



(a) (b) (c)

Fig. 10. (a) represents the grayscale of sample image 3, (b) represents surface plot, and (c) represents top view plot.

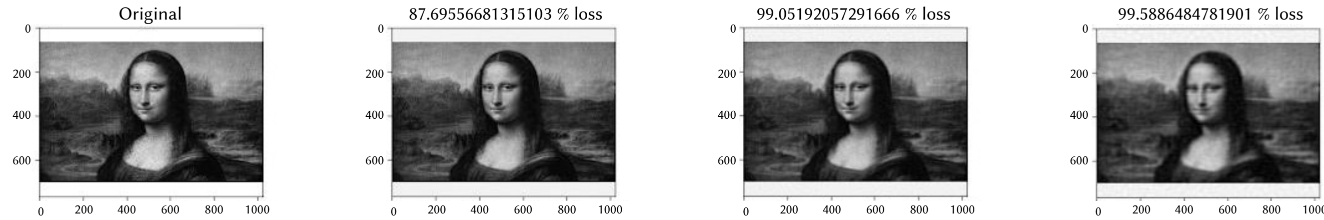
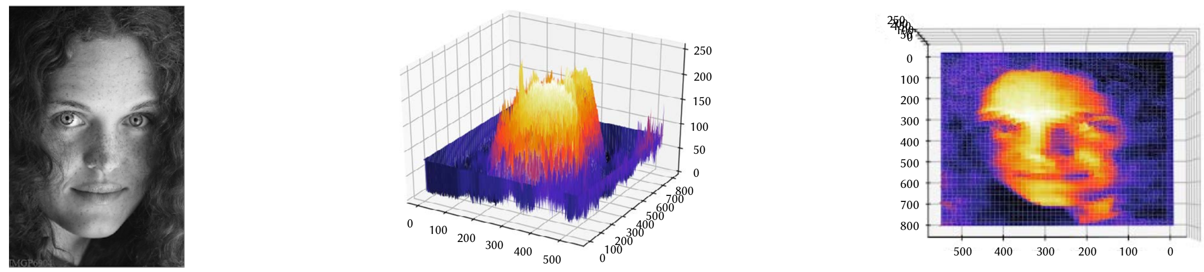


Fig. 11. Representations of the results of compression using Fourier transforms with the selected thresholds.



(a) (b) (c)

Fig. 12. (a) represents the grayscale image of sample image 4, (b) represents surface plot, and (c) represents top view plot.

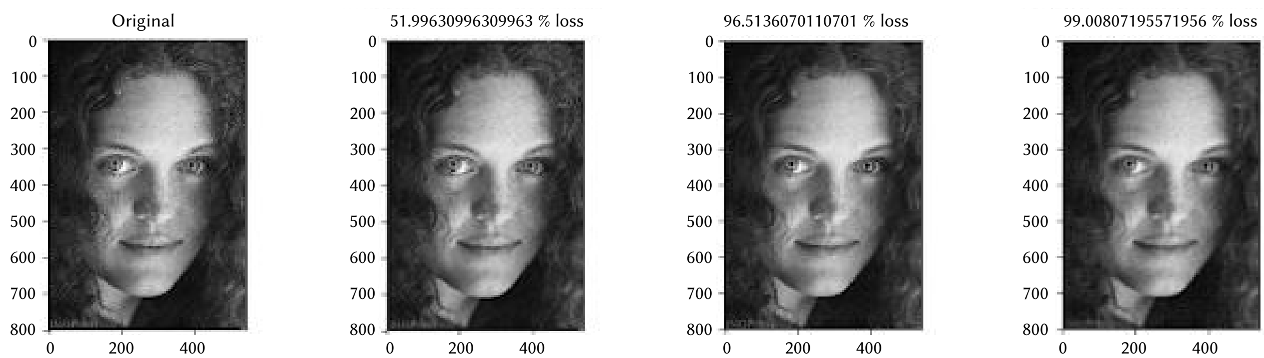


Fig. 13. Representations of the results of compression using Fourier transforms with the selected thresholds.

TABLE I. Data Loss and SSIM Score Comparison

Image	Compressed RGB image using threshold obtained using IWD		Compressed RGB image using standard method		Compressed RGB image using swapped values of threshold	
	SSIM Score	Data loss(%)	SSIM Score	Data loss(%)	SSIM Score	Data loss(%)
Sample image 1	0.69	99.8766642304	0.72	95.63583972020	0.60	95.63583972020
Sample image 2	0.73	99.7957887012	0.65	96.66549437568	0.65	95.95311462500
Sample image 3	0.88	99.7381844611	0.78	99.57618713378	0.69	96.58470153808
Sample image 4	0.62	98.9637915129	0.62	98.9637915129	0.65	79.35055350553

Hence, it is necessary to calculate thresholds based on the content of the image.

Table I shows the results of compressing images using the defined values and calculated values of thresholds for 4 different images of different color densities and structural formations. For sample image 1, using predefined values of (0.001, 0.001, 0.001) as p1, p2 and p3, the SSIM score after compression was found out to be 0.72 while the amount of data loss was over 95%. While using the values (0.001, 0.001, 0.01) which were obtained by IWD, the SSIM score was found out to be 0.69 while achieving a compression loss of more than 99.8%. To get a clear understanding of the result, we switched the values of the triplets to (0.01, 0.01, 0.001) and performed a compression. The image obtained had a SSIM score of 0.60 along with a 95% data loss. These results explain that, to achieve a maximum compression along with good quality for this particular image, the green channel must be kept along with blue being the least required. Which when violated, the result became unstable (see Table I: sample image 1).

VII. Conclusion

Image Compression which is the science of reducing the amount of data required to represent an image, is one of the most useful and commercially successful technologies in the field of digital image processing. Our assessment demonstrates that each compressed image must integrate the image content, thus improving the need to evaluate compression parameters for each image and whereby thresholds must be calculated for each image using IWD to compress images using fourier transform. Here we have constrained the values of these thresholds to be in a bounded parameter space. In future implementations, we wish to overcome the restricted parameter space implementation, i.e, the values that we used to begin the IWD search. We believe that, if an elaborated search space aka parameter space for the threshold values is provided to the IWD during its initialization, a better minimum can be found for our loss function thus improving the optimization strategy. Hence, we would like to introduce a bigger parameter space for finding the threshold values algorithm so as to increase the efficiency of the methodology and achieve better results.

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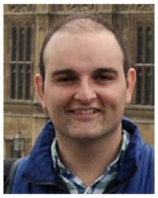

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