FRACTAL IMAGE COMPRESSION USING QUANTUM ALGORITHM

A PROJECT REPORT

Submitted by

JANANI T

Register No: 14MCO012

in partial fulfillment for the requirement of award of the degree

of

MASTER OF ENGINEERING

in

COMMUNICATION SYSTEMS

Department of Electronics and Communication Engineering

KUMARAGURU COLLEGE OF TECHNOLOGY

(An autonomous institution affiliated to Anna University, Chennai)

COIMBATORE - 641 049

ANNA UNIVERSITY: CHENNAI 600 025

APRIL 2016

FRACTAL IMAGE COMPRESSION USING QUANTUM ALGORITHM

A PROJECT REPORT

Submitted by

JANANI T

Register No: 14MCO012

in partial fulfillment for the requirement of award of the degree

of

MASTER OF ENGINEERING

in

COMMUNICATION SYSTEMS

Department of Electronics and Communication Engineering

KUMARAGURU COLLEGE OF TECHNOLOGY

(An autonomous institution affiliated to Anna University, Chennai)

COIMBATORE - 641 049

ANNA UNIVERSITY: CHENNAI 600 025

APRIL 2016

BONAFIDE CERTIFICATE

Certified that this project report titled **"FRACTAL IMAGE COMPRESSION USING QUANTUM ALGORITHM"** is the bonafide work of **JANANI.T [Reg. No. 14MCO012]** who carried out the research under my supervision. Certified further that, to the best of my knowledge the work reported herein does not form part of any other project or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

SIGNATURE

Dr. M. BHARATHI

PROJECT SUPERVISOR

Department of ECE

Kumaraguru College of Technology

Coimbatore-641 049

SIGNATURE

Dr. A.VASUKI

HEAD OF THE DEPARTMENT

Department of ECE

Kumaraguru College of Technology

Coimbatore-641 049

The Candidate with **Register No. 14MCO012** was examined by us in the project viva–voice examination held on............................

INTERNAL EXAMINER **EXTERNAL EXAMINER**

ACKNOWLEDGEMENT

First, I would like to express my praise and gratitude to the Lord, who has showered his grace and blessings enabling me to complete this project in an excellent manner.

I express my sincere thanks to the management of Kumaraguru College of Technology and Joint Correspondent **Shri Shankar Vanavarayar** for his kind support and for providing necessary facilities to carry out the work.

I would like to express my sincere thanks to our beloved Principal **Dr.R.S.Kumar Ph.D.,** Kumaraguru College of Technology, who encouraged me with his valuable thoughts.

I would like to thank **Dr.A.Vasuki Ph.D.,** Head of the Department, Electronics and Communication Engineering, for her kind support and for providing necessary facilities to carry out the project work.

In particular, I wish to thank with everlasting gratitude to the Project Coordinator **Dr.M.Alagumeenaakshi Ph.D.,** Assistant Professor-III, Department of Electronics and Communication Engineering, throughout the course of this project work.

I am greatly privileged to express my heartfelt thanks to my project guide **Dr.M.Bharathi Ph.D.,** Associate Professor, Department of Electronics and Communication Engineering, for her expert counselling and guidance to make this project to a great deal of success and I wish to convey my deep sense of gratitude to all teaching and non-teaching staff of ECE Department for their help and cooperation.

Finally, I thank my parents and my family members for giving me the moral support and abundant blessings in all of my activities and my dear friends who helped me to endure my difficult times with their unfailing support and warm wishes.

ABSTRACT

Fractal image compression (FIC) is an image coding technology based on the local similarity of image structure. FIC offers high compression ratio and good quality of retrieved images, which makes FIC a widely approved technology. However, fractal-based algorithms are strongly asymmetric because, in spite of the linearity of the decoding phase, the coding process is much more time consuming. Many algorithms have been developed to reduce the computational complexity involved in searching local self-similarities in an image. The proposed method, Grover's Quantum search algorithm (QSA) is optimal in search problems and achieves square-root speedup over classical algorithms in unsorted database searching. For this reasons, an attempt is made to apply Grover's QSA to FIC to reduce the computational complexity of FIC unprecedentedly.

To utilise quantum computing on FIC, a representation known as quantum representation is adopted on an image and is combined with Grover's search to yield a superior algorithm. The quantum superposition of image can create an enormously enhanced computing power. First, image is divided into two kinds of blocks namely, domain blocks and range blocks, and they are represented as quantum states. Then, Grover's QSA is employed to search the most similar domain block for each range block under the criterion of maximizing quantum fidelity between these two kinds of quantum states. The quantum fidelity calculated can reduce the minimum matching error between a given range block and its corresponding domain block, and thus, it can enhance the possibility of successful domain-range matching. A comparative analysis of existing DCT-FIC and proposed algorithm has been carried out using Compression ratio (CR), Computational complexity and PSNR. The experimental result shows that proposed algorithm achieves Compression ratio and PSNR 16% and 15% higher than DCT-FIC algorithm respectively. At the same time, Computational complexity is reduced to $O(\sqrt{N})$ in the proposed algorithm. In comparison with existing scheme which uses statistical parameter such as MSE to find the most similar block, the improved scheme therefore results in a considerable acceleration of the encoding process, enhanced retrieved image quality and good compression ratio.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

APCC	Absolute value of Pearson's Correlation Coefficient
CR	Compression Ratio
CT	Compression Time
D-BLOCK	Domain block
DCT-FIC	Discrete Cosine Transform FIC
DRDC	Deferring Range/Domain Comparison
FFT	Fast Fourier Tranform
FIC	Fractal Image Compression
FRQI	Flexible representation of Quantum Images
GPU	Graphics Processing Unit
HFPFIC	Huber Fitting Plane FIC
HVS	Human Visual system
IFS	Iterated Function System
JPEG	Joint Photographer's Experts Group
K-D TREE	K-Dimensional Tree
LS-FPFIC	Least Square regression-Fitting Plane FIC
MAD	Median Absolute Deviation
MSE	Mean Square Error
NEQR	Novel Enhanced Quantum Representation
PSNR	Peak Signal to Noise Ratio
QPFIC	Quad-tree Partition FIC
QSA	Quantum Search Algorithm
QUALPI	Quantum Log-Polar Image
R-BLOCK	Range Block
SQR	Simple Quantum Representation
SSIM	Structure Similarity Index

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW OF IMAGE COMPRESSION

The increasing demand for multimedia content such as digital images and video has led to great interest in research into compression techniques. The development of higher quality and less expensive image acquisition devices has produced steady increases in both image size and resolution, and a greater consequent for the design of efficient compression systems. Although storage capacity and transfer bandwidth has grown accordingly in recent years, many applications still require compression. In general, this thesis investigates still image compression in the spatial domain. Textures, Satellite and volumetric digital images are the main topics for analysis. The main objective is to design a compression system suitable for processing, storage and transmission, as well as providing acceptable computational complexity suitable for practical implementation [19]. The basic rule of compression is to reduce the numbers of bits needed to represent an image. In a computer an image is represented as an array of numbers, integers to be more specific, that is called as digital image. The image array is usually two dimensional (2D), if it is black and white (BW) and three dimensional (3D) if it is colour image. Digital image compression algorithms exploit the redundancy in an image so that it can be represented using a smaller number of bits while still maintaining acceptable visual quality.

Redundancy and Irrelevancy reduction is the two fundamental components of compression. Redundancy reduction aims at removing duplication from the signal source (image/video). Irrelevancy reduction omits part of the signal that will not be noticed by the signal receiver namely HVS (Human Visual System).

Factors related to the need for image compression include:

- Large storage requirements for multimedia data
- Low power devices such as handheld phones have small storage capacity
- Network bandwidths currently available for transmission
- Effect of computational complexity on practical implementation

1.2 FRACTAL IMAGE COMPRESSION

Fractal Image Compression (FIC) was first proposed by Michael Barnsley in 1987, who introduced basic principle of FIC. Self-similarity concept is the basis and premise of FIC. FIC is a technique which is used to encode the image in such a way that it reduces the storage space by using self-similar portion of the same image. FIC is a lossy compression technique for digital image, based on fractals. In certain images, some parts of the image resemble the other parts of same image, these self-similar parts are called fractal and these fractals are used in order to compress image. Fractal algorithms convert these parts (referred as fractals) or geometric shapes into mathematical information which is also called as 'fractal codes' which are later used to reconstruct an image. Once the image is converted into fractal code it becomes resolution independent. In the Figure.1.1 it is observed that whole image is repeated pattern of the part of the same image.

Figure.1.1 Fractal Fern

A general image has copies of parts of itself rather than the whole self. For example, the image Lena in Figure.1.2 has sample regions in the white squares. These sample regions are similar at different scales: a portion of her shoulder overlaps a region that is almost identical, and a portion of the reflection of the hat in the mirror is similar to a part of her hat.

Figure.1.2 Lena Image with Self-similarities at different scale

FIC is a block based image compression, detecting and coding the existing similarities between different regions in the image. For conventional fractal compression schemes, an image is partitioned into domain blocks and range blocks, the self-similarities exploiting between these two kinds of blocks in the spatial domain is computationally expensive, usually hundreds of seconds is used to encoding an image, which restricts the application of fractal image compression [11].

The process of fractal image coding is finding the appropriate domain block for each range block using Iterated function system (IFS) mapping. In IFS mapping, coefficient will represent a data of block of the compressed image. Thus a digitized image can be stored as a collection of Iterated function system (IFS) transformations parameters and is easily regenerated or decoded for use or display. The storage of the IFS transformation coefficients results in relatively high compression ratios and good reconstruction fidelity. Figure.1.3 illustrates the storage of IFS transformation coefficients along with fractal structure.

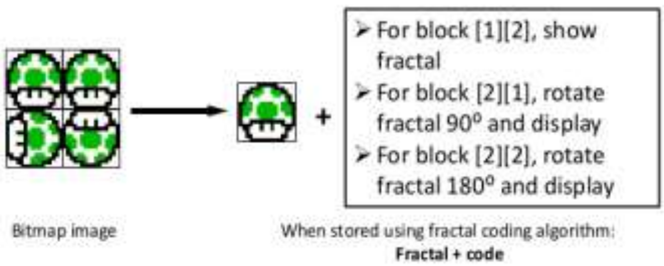

Figure.1.3 Fractal Image and Storage of IFS Transformation coefficients with Fractal Structure

1.2.1 Merits and Demerits of FIC

When compared to other compression method which is used for compressing different kind of images, FIC has some main advantages and drawbacks.

Merits:

• Mathematical encoding frame is good

• Resolution independent

• Achieves high compression ratio

• Fast decoding

Demerits:

• Encoding speed is slow

1.2.2 Motivation and Problem Statement

FIC suffers from high computational cost in searching local self-similarities in natural image. Recent studies aims at speeding up FIC using pre-processing tools or approximation methods. But reducing the intrinsic computational complexity of FIC is still an open problem. Motivated by this, an algorithm based on quantum computing is introduced to reduce the intrinsic computational complexity in searching local self-similarities.

1.2.3 Objectives

The main objective of the project is to reduce the intrinsic computational complexity using Quantum based FIC. The sub objective is to maintain quality of retrieved images without sacrificing compression ratio and to compare the performance of the proposed algorithm with existing algorithm such as DCT-FIC.

1.3 INTRODUCTION TO QUANTUM COMPUTING

Quantum computing is a promising approach of computation that is based on equations from Quantum Mechanics. The idea of a quantum computer was first proposed in 1981 by Nobel laureate Richard Feynman, who pointed out that accurately and efficiently simulating quantum mechanical systems would be impossible on a classical computer, but that a new kind of machine, a computer itself “built of quantum mechanical elements which obey quantum mechanical laws", might one day perform efficient simulations of quantum systems. Classical computers are inherently unable to simulate such a system using sub-exponential time and space complexity due to the exponential growth of the amount of data required to completely represent a quantum system. Quantum computers, on the other hand, exploit the unique, non-classical properties of the quantum systems from which they are built, allowing them to process exponentially large quantities of information in only polynomial time. Of course, this kind of computational power could have applications to a multitude of problems outside quantum mechanics, and in the same way that classical computation quickly branched away from its narrow beginnings facilitating simulations of Newtonian mechanics, the study of quantum algorithms has diverged greatly from simply simulating quantum physical systems to impact a wide variety of fields, including information theory, cryptography, language theory, and mathematics.

1.3.1 Fundamental difference in Mathematical representation

Quantum computers employ the laws of quantum mechanics to provide a vastly different mechanism for computation than that available from classical machines. Fortunately for computer scientists interested in the field of quantum computing, a deep knowledge of quantum physics is not a prerequisite for understanding quantum algorithms, in the same way that one need not know how to build a processor in order to design classical algorithms. However, it is still important to be familiar with the basic concepts that differentiate quantum mechanical systems from classical ones in order to gain a better intuitive understanding of the mathematics of quantum computation, as well as of the algorithms themselves [48].

The first distinguishing trait of a quantum system is known as superposition, or more formally the superposition principle of quantum mechanics [22]. Rather than existing in one distinct state at a time, a quantum system is actually in all of its possible states at the same time. With respect to a quantum computer, this means that a quantum register exists in a superposition of all its possible configurations of 0's and 1's at the same time, unlike a classical system whose register contain only one value at any given time. It is not until the system is observed that it collapses into an observable, definite classical state.

It is still possible to compute using such a seemingly unruly system because probabilities can be assigned to each of the possible states of the system. Thus a quantum system is probabilistic: there is a computable probability corresponding to the likelihood that that any given state will be observed if the system is measured. Quantum computation is performed by increasing the probability of observing the correct state to a sufficiently high value so that the correct answer may be found with a reasonable amount of certainty.

Quantum systems may also exhibit entanglement [25]. A state is considered entangled, if it cannot be decomposed into its more fundamental parts. In other words, two distinct elements of a system are entangled if one part cannot be described without taking the other part into consideration. In a quantum computer, it is possible for the probability of observing a given configuration of two qubits to depend on the probability of observing another possible configuration of those qubits, and it is impossible to describe the probability of observing one configuration without considering the other. An especially interesting quality of quantum entanglement is that elements of a quantum system may be entangled even when they are separated by considerable space. The exact physics of quantum entanglement remain elusive even to professionals in the field, but that has not stopped them from applying entanglement to quantum information theory. Quantum teleportation, an important concept in the field of quantum cryptography, relies on entangled quantum states to send quantum information adequately accurately and over relatively long distances.

1.3.2 Quantum Algorithms

There is a wealth of interesting and important algorithms have been developed for quantum computers. The algorithms like Shor’s algorithm, Grover’s algorithm and Simon’s algorithm can be reviewed in order to better elucidate the study of quantum computing theory and quantum algorithm design. These algorithms are good models for current understanding of quantum computation as many other quantum algorithms use similar techniques to achieve their results, whether it is an algorithm to solve linear systems of equations, or quickly compute discrete logarithms.

The algorithm that is explored here is Lov Grover's quantum database search. Classically, searching an unsorted database requires a linear search, which is $O(N)$ in time. Grover's algorithm, which takes $O(N^{1/2})$ time, is the fastest possible quantum algorithm for searching an unsorted database. It provides "only" a quadratic speedup, unlike other quantum algorithms, which can provide an exponential speedup over their classical counterparts. However, even quadratic speedup is considerable when N is large.

Like all quantum computer algorithms, Grover's algorithm is probabilistic, in the sense that it gives the correct answer with high probability. The probability of failure can be decreased by repeating the algorithm.

1.3.3 Uses of Grover's algorithm

Although the purpose of Grover's algorithm is usually described as searching a database, it may be more accurate to describe it as inverting a function. Roughly speaking, if we have a function $y=f(x)$ that can be evaluated on a quantum computer, Grover's algorithm allows us to calculate x when given y. Inverting a function is related to the searching of a database because we could come up with a function that produces a particular value of y if x matches a desired entry in a database, and another value of y for other values of x.

The entire project report is structured as follows. In Chapter II, the techniques in the literature related to fractal image compression (FIC) are reviewed. In Chapter III, few existing algorithm is introduced and the comparative analysis is made on the existing algorithms. In Chapter IV, focus is on the flow of proposed algorithm and several optimization methods involved in the proposed scheme. The experiment results are shown in Chapter V. Finally, the conclusions are drawn in Chapter VI.

CHAPTER 2

LITERATURE SURVEY

The significant computational requirements of the domain search resulted in lengthy coding times for early fractal compression algorithms. The design of efficient domain search techniques has consequently been one the most active areas of research in fractal coding, resulting in a wide variety of solutions. The various techniques in the literature related to fractal image compression (FIC) are reviewed to improve the efficiency of FIC.

Invariant representation

In [1], the search for the best domain block for a particular range block is complicated by the requirement that the range matches a transformed version of a domain block; the problem is in fact to find for each range block, the domain block that can be made the closest by an admissible transform. The problem may be simplified by constructing an appropriate invariant representation for each image block. Transforming range and contracted domain blocks to this representation allows direct distance comparisons between them to determine the best possible match.

In [2], Invariant representations for the single constant block transform utilise the DCT (or another orthogonal transform) of the vector followed by zeroing of the DC term and normalisation. This representation can decrease the time required for an efficient domain search, and allows the utilisation of a distance measure adapted to the properties of the human visual system.

In [3], FFT based fractal image coding with variable quad-tree partition is used. This algorithm is applied to the approximation sub-band and three detail sub-bands of the wavelet transformed image. Quad-tree partitioned wavelet sub-tree is constructed after wavelet decomposition of fractal decoded approximation sub-band image. The self-similarities existing in wavelet sub-tree are exploited by predicting the coefficients at finer scale from those at coarser scale using affine transformation.

In conventional fractal coding algorithm the main drawbacks are high encoding time, blocking artefacts at low bit rates. These twin drawbacks can be avoided if fractal transformation is in the wavelet domain. Many authors combined wavelets with fractal coding to obtain high quality for compression at low bit rate. The objective of combining wavelet and fractal coding is to increase the encoding speed and high compression ratio than pure fast fractal algorithm. Wavelet transform perform decomposition of image signals into multi resolution with set of tree structured coefficients. These coefficients have the same spatial location with different resolution and orientation. In wavelet transform based fractal coding, the high frequency coefficients of one level is predicted from the next level sub-band coefficients because they are highly correlated. Fast fractal encoding, normalized cross correlation with mean square error (MSE) as matching criteria is applied to only low frequency components using quad-tree partition. Other wavelet coefficients are predicted using non iterative fractal coding with variable size sub-tree representation. This helps to improve the visual quality without blocking artefacts at low bit rates than JPEG. Regarding speed, the proposed method presents an average 92% reduction of coding time comparing to the fast fractal image coding. But the main drawback in proposed method is that, for high bitrates, the visual quality is poor as there is blocking artefacts.

Furao & Hasegawa [4,] has proposed fractal coding method based on without search. Wavelets transform and Diamond search based hybrid fractal coding proposed by Zhang [5]. Chen [6] proposed Kick-out method to discard impossible domain blocks based on one–norm in early stage of current range block is used, in this method for the comparison of range and domain blocks normalization of range and domain block is performed.

In parallel approach by Palazzari [7] the image is divided into blocks each block is processed by the one processor. Each processor executes sequential algorithm on its block and returns the result. Limitation of this approach is it uses coarse grained input data. i.e., each processor only works on the subset of domain blocks this result in insufficient mapping. So the resultant image will be inferior to sequential approach. In this method diamond search is applied to find matching domain block with range block, like motion estimation technique in video compression.

GPU based fractal image compression for medical imaging is demonstrated [8]. Results show drastic reduction in encoding time due to use of parallel approach. Cluster of GPU is used for fractal image compression by Chauhan [9]. In this approach domain pool is divided on to slave machines by master node and range blocks are circulated in pipelined manner across all slaves till the match is found. If match is not found then master divides the range and re-circulate it.

Fitting Plane

In [10], based on Wang's fitting plane-based fractal image coding using least square regression (LS-FPFIC), Jian Lu, Zhongxing Ye and Yuru Zou proposes an efficient Huber fitting plane-based fractal image compression method (HFPFIC). In the HFPFIC, by building Huber fitting planes for the domain and range blocks, a new matching error function is proposed to avoid that the corrupted data is present as the independent variable in the Huber regression model, and a weighted operator is utilized to eliminate the influence of outliers on evaluating the matching error. Since the Huber fitting planes for all domain blocks are calculated in advance before the matching process is carried out, the number of robust regression-iterations for full search HFPFIC is considerably reduced when comparing to the other full search robust FIC methods.

Furthermore, this paper proposes a normalized median absolute deviation about the median (MAD) decomposition criterion used as adaptive quad-tree partitioning scheme, which works very fast and achieves very nice partitioning results both for noiseless and salt & pepper noisy images. In order to relieve the high computational complexity, the no-search scheme is utilized to accelerate the encoding process. The results show that, especially for the noisy image corrupted by salt & pepper noise, compared with conventional robust fractal image coding methods, the proposed algorithm can save the encoding time and improve the restored image quality efficiently. It is shown that, when applying the Huber fitting plane (HFP) technique to encode the corrupted image directly, it can achieve good image quality and extremely fast encoding speed.

Though FIC methods achieved robustness against the outliers caused by salt & pepper noise they do not show significant improvement in image quality for Gaussian and Laplace noises. However, these robust FIC methods are not quite satisfactory. Besides the high computational cost, the domain block containing hidden outliers under the samples is used as the independent variable in the robust regression model, which may negatively influence the performance of the robust estimator for the computation of the fractal parameters.

Classification

Classification based search techniques often do not explicitly utilise an invariant representation as formalised above, but rely instead on features which are at least approximately invariant to the transforms applied. Domain and range blocks may either be classified into a fixed number of classes according to these features[11][12], a matching domain for each range only being sought within the same class, or inspection of domains may be restricted to those with feature values close to those of the range.

In [13], a novel fractal compression scheme to meet both the efficiency and the reconstructed image quality requirements is proposed. This scheme is based on the fact that the affine similarity between two image blocks is equivalent to the absolute value of Pearson's correlation coefficient (APCC) between them. Firstly, all the domain blocks are classified into 3 classes according to the classification method. Secondly, the domain blocks are with respect to APCCs between these domain blocks and a preset block in each class, and then the matching domain block for a range block can be searched in the selected domain set in which these APCCs are closer to APCC between the range block and the preset block. Since both the steps in our scheme are based on APCC which is equivalent to the affine similarity in FIC, the reconstructed image quality is well preserved. Moreover, the encoding time is significantly reduced in our APCC-based FIC scheme. The block D satisfying $|\rho(R,D)| \to 1$ is usually hard to search for R, it is important to choose a proper block as the preset block B to search the best approximate D.

Hassaballah [14] used Entropy based approach to classify the domain blocks. Fidelity of reconstructed image is poor in this case. Wang [13] used absolute value of Pearson correlation coefficient to classify domain blocks. Range blocks restricted to search in area of sorted list where correlation is maximum.

It is evident that the algorithm performs better than the baseline algorithm in terms of time and PSNR. However, one of the difficulties with fractal coding is that its faster implementations tend to be a little memory-hungry. Therefore, it is interesting to consider the methods under exam from the point of view of memory usage, showing in what circumstances the domain tree results in memory savings respect to the other spatial access methods.

Segmentation

In [15], Kamel Belloulata and Janusz Konrad explore fractal image coding in the context of region-based functionality with two region-based fractal coding schemes implemented in spatial and transform domains, respectively. In both approaches regions are defined by a prior segmentation map and are fractal-encoded independently of each other. A new dissimilarity measure is proposed that is limited to single-region pixels of the range block. The computational complexity of encoding an image using the proposed method is directly related to the size of search space over which the distortion is minimized; the number of permissible domain blocks plays the dominant role. The most demanding case is when each segment of every domain block of the image is considered; the domain-block codebook is built from the whole image. This exhaustive procedure is theoretically optimal but extremely involved computationally. Moreover, it does not allow for independent decoding of regions.

In DCT-based fractal coding, boundary range blocks contain pixels from two or more objects. Thus, similarly to the spatial-domain case, independent decoding of objects is not possible. Also, the coding quality may suffer since pixels on different sides of the boundary may have different characteristics; by applying the standard DCT to such a block, spectral properties of these pixels are mixed up making the search for a good range-domain correspondence unreliable. In particular, a sharp intensity transition may cause significant spectral oscillations. Wang Hai [16] proposed Graph-based image segmentation approach to separate an input image into many different logic areas according to image content and to construct search space for each logic area. Each logic area is encoded using adaptive threshold quad-tree approach for fast image compression.

Feature Extraction

In [17] Riccardo Distasi, Michele Nappi, and Daniel Riccio proposed a new approach, namely deferring range/domain comparison (DRDC), based on feature vectors. The main idea is to defer the comparisons between ranges and domains. Rather, a preset block is used as a temporary replacement. The preset block is computed as the average of the ranges present in the image. The coding phase is divided in two phases.

In the first phase, where the domain codebook is created, all the domains are extracted from the image, then each of them is compared with the preset block by solving a mean square root problem. The preset block/domain approximation error is computed and stored in a KD-tree data structure. In the second phase, the ranges have to be encoded; each one of them is compared with the preset block, thus obtaining the preset block/range approximation error, in the same way as performed for domains. Using this data, it is found the domains that are likely to encode the current range with the best accuracy. This criterion proves that a generic range block is accurately coded by domains with equal or similar approximation error. In this way, for each range we have to perform a much smaller number of range/domain comparisons, and the time spent for coding is significantly reduced.

Kung [18] used one dimensional DCT for feature extraction and blocks are classified into 4 types of edges. The structure similarity (SSIM) index is used instead of MSE to reduce computation complexity.

Quantum Based Methods

Venegas-Andraca and Bose [19] introduced image representation on the quantum computers by proposing the ‘qubit lattice’ method, in which each pixel was represented in its quantum state and then a quantum matrix was created with them.

The ’qubit lattice’ representation was incorporated by Yuan [20] in their simple quantum representation (SQR) method for infrared images. The SQR method replaced the color information with the radiation values as the coefficient values.

Inspired by ‘qubit lattice’, Li [21] proposed a quantum representation of images which explicitly included and encoded the pixel position along with the color information. Subsequently, Li [22-23] extended their previous works to multidimensional color images using quantum super position. However, these methods [21-23] are constrained by qubit angle that has upper bound for the number of values it can possess. The qubit angle encodes the color information and is highly dependent on the image dimensions and the bit depth of color.

In another work, Venegas-Andraca and Ball [24] proposed an ‘entangled image’ method for representing shapes in binary images through quantum entanglement. They only concentrated on binary images, whereas real life images possess multiple intensity levels. Both ‘qubit lattice’ and ‘entangled image’ are the quantum analog of classical images, and do not utilize the superposition property of quantum computation to represent all the pixels together.

Latorre [25] proposed the ‘real ket’ approach that used quad-tree to locate each pixel using 4-D qubit sequence. In order to be efficient, ‘real ket’ requires image pixel values to be random, which is rare as images are highly correlated.

Le [26, 27] provided a flexible representation of quantum images (FRQI) for multiple intensity levels in a 2-D pixel representation, enabling various image processing operations and applications.

Sun [28, 33] expanded FRQI into three color channel RGB image. Through novel enhanced quantum representation (NEQR), Zhang [29] (also independently proposed by Caraiman and Manta [34]) provided an alternate approach to FRQI by storing the intensity information into qubits, along with the pixel information at the cost of increasing the number of qubits. Moreover, this method can only represent images with unsigned integer values.

In a separate work, Zhang [35] also presented a quantum image representation method, named quantum log-polar image (QUALPI), for the unsigned integer images acquired in the log-polar coordinate system.

Among all the above methods, FRQI and NEQR are most comprehensive and have been used to develop many image processing applications [21-29], [34-47]. A detailed literature survey can be found in [48, 49].

However, one of the difficulties with quantum based method is that, when the domain-range block size is reduced to improve compression ratio, it tends to be computationally expensive in searching similarities. Therefore, it is interesting to consider the methods under exam from the point of view of reducing computational complexity in searching self-similarities. A possible approach could be use of Grover's search with quantum representation.

CHAPTER 3

EXISTING METHOD

3.1 FRACTAL CODING ALGORITHMS

Fractal coding is a method of image compression. The main principle of the fractal transform coding is based on the hypothesis that the image redundancies can be efficiently exploited by means of block self-affine transformations. By removing the redundancy related to self-similarity in an image. Fractal image compression can achieve a higher compression ratio with high decoding quality. Fractal coding has the advantage such as resolution independence and fast decoding as compare to other image compression methods. So fractal image compression is a promising technique that has great potential to improve the efficiency of image storage and image transmission. The problem with fractal coding is the highly computational complexity in the encoding process. Few Fractal coding algorithms that focus on reducing encoding complexity are,

- Quad-tree Decomposition and Huffman Coding
- DCT Based Fractal Image Compression

3.1.1 Quad-tree Decomposition and Huffman Coding

Quad-tree Decomposition is one of the partition based methods. It divides an image into variable size range block. In this type of partition, a square image is split into square blocks of equal sizes, and then tests each block to check whether each block meets some criteria of homogeneity. If a block meets the criteria it is not divided any further, if the block does not meet the criteria, then the block is splited into further four blocks and again test is applied to those blocks. This process is repeated iteratively until each and every block meets the criteria resulting in many different sizes of blocks. It is represented in a tree like structure, where each node will have four sub nodes. Adjustment of quad-tree size is done by using two parameters, minimum level and maximum level. By this method it is possible to increase the compression ratio and reduce the bits used to represent an image i.e. bits per pixel (bpp). Huffman coding method was introduced by D.A.Huffman. This is used to remove the redundancy in the image. In this algorithm the probability of all alphabet symbols are arranged in decreasing order. Then it constructs from the bottom up, a binary tree with a symbol at every leaf node. This is done in steps, where in each step two symbols with the smallest probability are chosen and added, placed in the top of the tree and then deleted from the list, and replaced with another symbol representing the two original symbols. This is repeated until only two symbols are retained at the end of the tree. Finally to determine the codeword's of the symbols the tree is traversed from leaf node to root node. It is a variable length coding. According to this algorithm, the symbols with small frequency will have long code words and vice-versa.

Algorithm steps:

1. Divide the original image using Quad-tree decomposition of threshold 0.2, minimum Dimension and maximum dimension of 2 and 64 respectively.

2. Record the values of x and y coordinates, mean value and block size from Quad-tree Decomposition.

3. Record the fractal coding information to complete encoding of the image using Huffman coding and then calculate the compression ratio.

4. For the encoded image, apply Huffman decoding to reconstruct the image and calculate PSNR as shown in Figure.3.1.

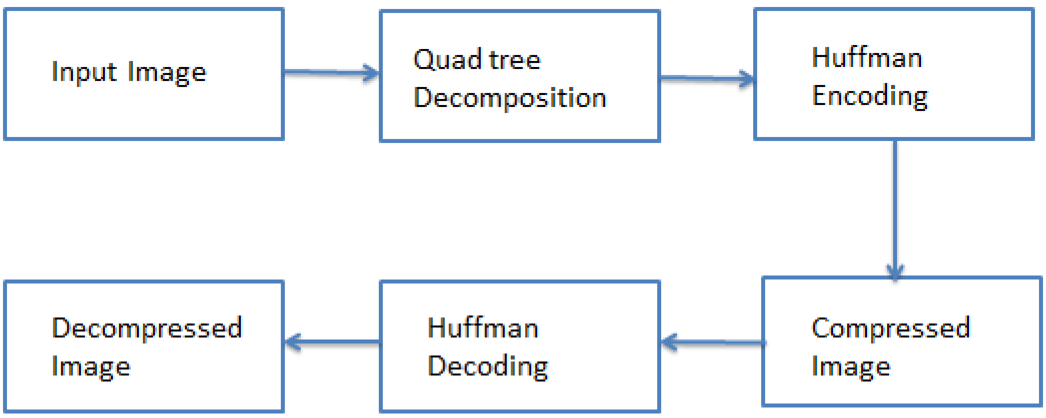

Figure.3.1 QDHC Fractal Compression Technique

3.1.2 DCT Based Fractal Image Compression

To improve the fractal encoding speed, this algorithm proposes a new block classification method based on the edge characteristic of an image block. The essence of this method is that if the domain block has the same edge characteristic to the range block then they are similar in fractal meanings. By restricting the exploiting range of domain block, this method can not only fasten the fractal encoding speed, but also guarantee the quality of the decoded image. In DCT coefficients, lower frequency coefficients represent the main energy of an image, while the higher frequency coefficients represent the edge information. Therefore if two image blocks are similar besides some detailed information, then their DCT lower frequency coefficients are approximately equal. So it is sufficient to use lower coefficient for evaluating the similarity degree between two image blocks [2].

Algorithm steps:

(1) Image partition

Let I be a gray-scale image to be encoded. Partition I into a set of $B\times B$ pixels range blocks, which are non-overlapping and overlay the whole image. Image I is also partitioned into a set of $2B\times 2B$ pixels domain blocks, which can be overlapping and need not overlay the whole image. The D block partition process can be done by sliding a $2B\times 2B$ window from left to right, top to bottom with horizontal step δ_h and vertical step δ_v. Here $\delta_h = \delta_v = B$.

(2) Best match exploiting

After R blocks and D blocks are constructed, the next step is exploiting best match for each R block. First, each D block is compressed in spatial domain to reduced block D', which has the same size to R block. The compression method is reducing four adjacent pixels to one pixel, whose gray-scale is the average of the four pixels. The matching process is selecting a block Ri, then finding a Dj block with the same class as the block Ri, 8 isometric transformation are done for each Dj block, as shown in table.3.1.

The best matching D block for R block is determined by evaluating the MSE (Mean Square Error) between Ri and each Dj with 8 isometric transformation. The minimum MSE means the best match. The MSE is determined by

$$MSE = \frac{\sum_{k=1}^{N}[r_k - s_i.d'_k + o_i]^2}{N}, (N = BXB) \qquad (3.1)$$

where the contrast factor *si* is

$$s_i = \frac{n(\sum_{k=1}^{n} r_k d_k{'}) - (\sum_{k=1}^{n} d_k{'})(\sum_{k=1}^{n} r_k)}{n\sum_{k=1}^{n} d_k{'}^2 - (\sum_{k=1}^{n} d_k{'})^2} \qquad (3.2)$$

and the brightness factor *oi* is

$$o_i = \frac{1}{n}(\sum_{k=1}^{n} r_k - s_i \sum_{k=1}^{n} d_k{'}) \qquad (3.3)$$

Table.3.1 Eight Isometric transformation

No.	Matrix	Explanation
1	$\begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$	identical transformation
2	$\begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix}$	*Y* axis based reflection
3	$\begin{pmatrix} -1 & 0 \\ 0 & 1 \end{pmatrix}$	*X* axis based reflection
4	$\begin{pmatrix} -1 & 0 \\ 0 & -1 \end{pmatrix}$	180 degree rotation
5	$\begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$	*Y*=*X* axis based reflection
6	$\begin{pmatrix} 0 & 1 \\ -1 & 0 \end{pmatrix}$	90 degree rotation
7	$\begin{pmatrix} 0 & -1 \\ 1 & 0 \end{pmatrix}$	270 degree rotation
8	$\begin{pmatrix} 0 & -1 \\ -1 & 0 \end{pmatrix}$	*Y*=-*X* axis based reflection

Finally, the four parameters of the best match *D* block constructs the fractal code, they are position of the block, isometric transformation number, contrast factor and brightness factor.

3.2 COMPARATIVE ANALYSIS

Figure.3.2 Comparison of visual image quality of reconstructed image for QDHC and DCT respectively

Original and reconstructed images for the two algorithms are shown in Figure.3.2. It can be seen that DCT-FIC based reconstructed image quality is better than the QDHC algorithm based reconstructed image.

Table.3.2 and Table.3.3 gives the obtained Compression ratio, PSNR and Compression Time for the QDHC algorithm and DCT-FIC algorithm respectively. The values are tabulated for three kinds of image: Lena image, Texture image and Satellite Image. It is observed that, in both the algorithms Compression ratio and PSNR obtained for fractal geometry based image is higher than that of Lena image.

Table.3.2 Quad-tree Decomposition and Huffman Coding

Image(512X512)	**Compression ratio**	**Compression Time**	**PSNR**
Lena	10.115922	1.849794 seconds	25.692002
Texture	17.826862	1.947244 seconds	28.047388
Satellite	25.647588	0.780619 seconds	27.735443

Table.3.3 DCT based Fractal Image Compression

Image(512X512)	Compression ratio	Compression Time	PSNR
Lena	37.4391	2.084829 seconds	34.0181280
Texture	22.5821	4.295735 seconds	38.3627523
Satellite	27.8954	3.689613 seconds	34.3149391

It can be seen from Figure.3.3 and Figure.3.4 the compression ratio CR is high for DCT-FIC as compare to QDHC, without degrading quality of reconstructed image. Though, it is seen that from Figure.3.5 DCT-FIC has larger compression time than the QDHC, it is considered to be more efficient on concerning domain-range based search algorithms.

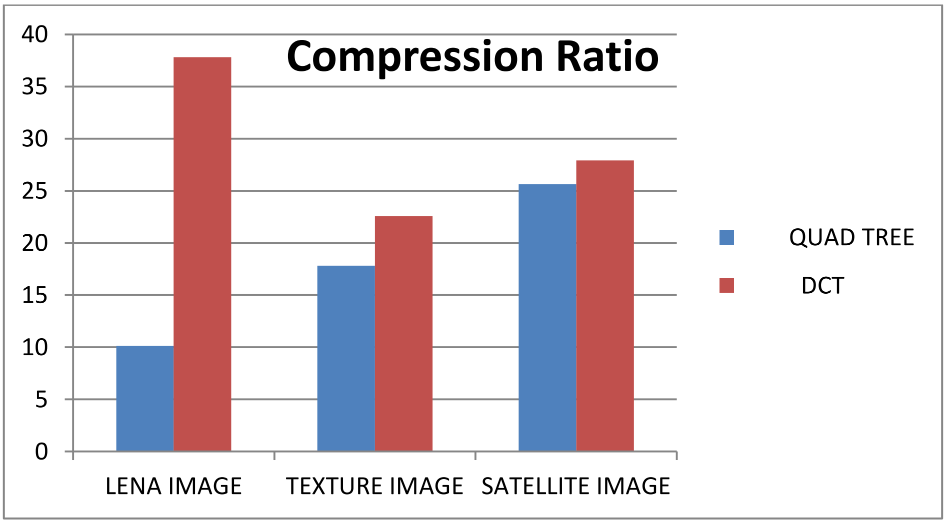

Figure.3.3 Comparison graph based on compression ratio

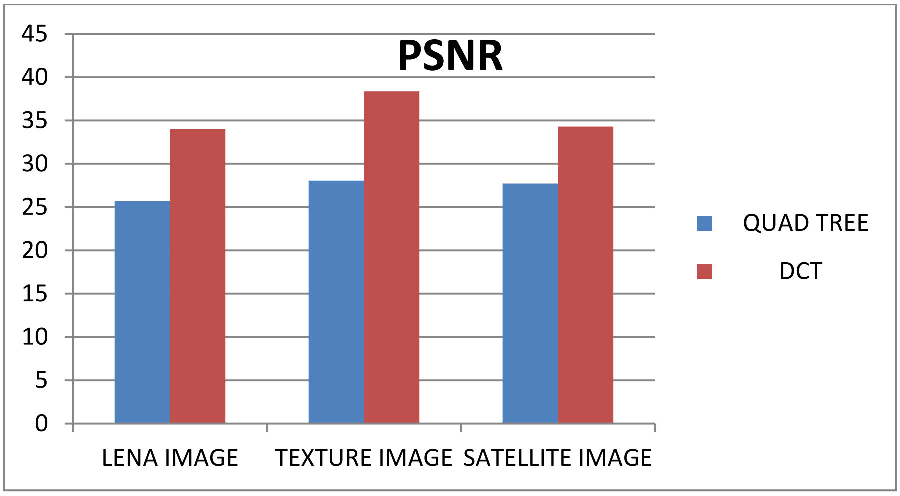

Figure.3.4. Comparison graph based on PSNR

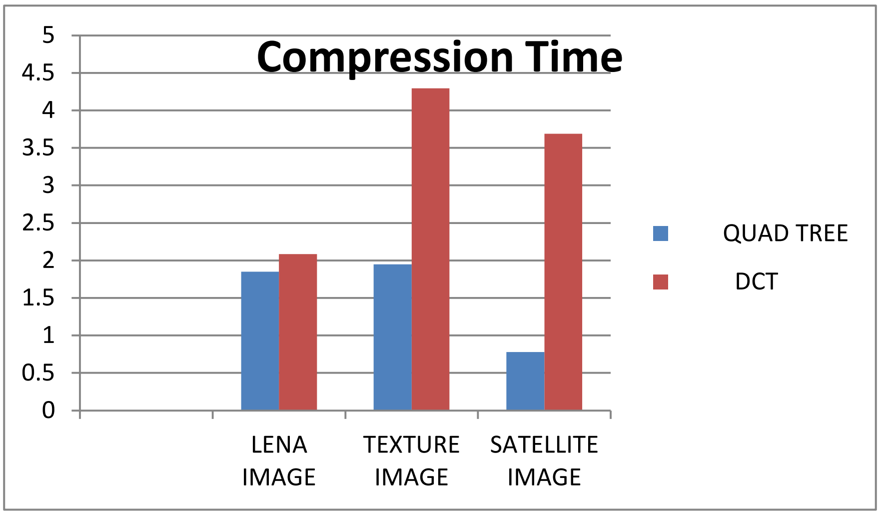

Figure.3.5 Comparison graph based on compression time

CHAPTER 4

PROPOSED METHOD

4.1 QUANTUM BASED FRACTAL CODING ALGORITHM

Quantum computation is the field that investigates the computational power of computer based on quantum-mechanical principles. In recent times, there has been significant progress in quantum computing. Richard Feynman, who was interested in using a computer to simulate quantum systems, first investigated using quantum systems to do computation in 1982. He realized that the classical storage requirements for quantum systems grow exponentially in the number of particles. So while simulating twenty quantum particles only requires storing a million values, doubling this to a forty particle simulation would require a trillion values. Interesting simulations, say using a hundred or thousand particles, would not be possible, even using every computer on the planet. Thus he suggested making computers that utilized quantum particles as a computational resource that could simulate general quantum systems in order to do large simulations, and the idea of using quantum mechanical effects to do computation was born.

The exponential storage capacity, coupled with some spooky effects like quantum entanglement, has led researchers to probe deeper into the computing power of quantum systems. Here, the idea of quantum computing is brought into FIC, to utilize quantum particles as a computational resource in order to reduce search complexity in FIC [34].

The three key steps of quantum based FIC algorithm are, partition and transformation, quantum representation of classical image, and search optimal fractal code.

- Partition and Transformation**:**

Let I be a gray-scale image to be encoded. Partition I into a set of B×B pixels range blocks, which are non-overlapping and overlay the whole image.

$$I = \cup_{i=1}^{N} R_i \, , R_i \cap R_i = \emptyset(i \neq j), i = 1,2,..,N \tag{4.1}$$

Image I is also partitioned into a set of $2B \times 2B$ pixels domain blocks, which can be overlapping and need not overlay the whole image. The D block partition process can be done by sliding a $2B \times 2B$ window from left to right, top to bottom with horizontal step δh and vertical step δv. Here, $\delta h = \delta v = B$. The size of the range pool can be easily calculated by dividing $M\ X\ N$ by$B\ X\ B$, and the size of the domain pool should be $M - 2B + 1\ X\ N - 2B + 1$. Subsequently, all domain blocks are contracted into the same size with range blocks by a spatial contraction, such as averaging four pixels to one pixel.

- Quantum Representation of Classical Image:

A novel method to represent classical images as normalized quantum states is proposed [26]. It represents image using two-dimensional (2- D) quantum states to locate each pixel in an image through row-location and column-location vectors.

The dual representation of a 2-D image by the row-location and column location vectors is achieved by generating M-length row location vector and N-length column-location vector with m-qubits and n-qubits, respectively, where $m = \log_2 M$ and $n = \log_2 N$. To represent a pixel location in its 2-D matrix and to identify 2-D location of a pixel, the tensor product of the row-location vector and the column-location vector is carried out as follows,

$$L_{p,q} = |I\rangle_p \otimes \langle J|_q \tag{4.2}$$

Where, $L_{p,q}$ is the 2-D quantum state of a pixel at pth row and qth column using m-qubits and n-qubits, respectively. The next feature is the incorporation of pixel amplitude/intensity values into the scalar amplitude of its respective 2-D quantum state, requiring no additional qubits. In the quantum computation theory, the scalar amplitudes (α) of the quantum states [23], like the quantum states and the superposition of quantum states, are also constrained to be unit vector, i.e.

$$\sum_{p=1}^{M} \sum_{q=1}^{N} {\alpha^2}_{p,q} = 1 \tag{4.3}$$

Where, $\alpha_{p,q}$ is the scalar amplitude of the pixel quantum state at p^{th} row and q^{th} column. Let $A_{p,q}$ be the amplitude/intensity of the pixel at p^{th} row and q^{th} column. To incorporate $A_{p,q}$ into $\alpha_{p,q}$ such that above equation is satisfied, $\alpha_{p,q}$ can be written as,

$$\alpha_{p,q} = \sqrt{\frac{A_{p,q}}{\sum_{p=1}^{M}\sum_{q=1}^{N} A_{p,q}}} \tag{4.4}$$

As can be seen, $A_{p,q}$ is normalized with respect to total amplitude ${A_T}^{MXN} = \sum_{p=1}^{M}\sum_{q=1}^{N} A_{p,q}$, in order to be used as $\alpha_{p,q}$. It must be noted that $A_{p,q}$ can possess any value, whether unsigned integer or real values for gray scale images and the individual channels of color images.

Now incorporate these structures for representation of domain and range blocks as quantum states. Making the use the 2-D quantum state representation of each pixel and its scalar amplitude, the quantum blocks can be represented as the superposition of all the pixel's quantum states along with their scalar amplitudes. The range block representation, is defined as,

$$|R\rangle = \sum_{p=1}^{B}\sum_{q=1}^{B} \alpha_{p,q}\, L_{p,q} \tag{4.5}$$

After substituting $L_{p,q}$ and $\alpha_{p,q}$, the above can be rewritten as,

$$|R\rangle = \frac{1}{\sqrt{{A_T}^{BXB}}}\sum_{p=1}^{B}\sum_{q=1}^{B} \sqrt{A_{p,q}}\, (|I\rangle_p \otimes \langle J|_q) \tag{4.6}$$

Similar representation is followed for the domain block $|D\rangle$ with spatially contracted size$B\ X\ B$.

Since a quantum bit can be effectively represented by a two-dimensional vector in a complex vector space, the above sequence of equations can be expediently implemented as two-dimensional vectors by programming with Matlab. After quantum representation, the rest operations of the algorithm can be implemented by means of matrix manipulations.

- Search optimal fractal code:

Based on the above preparations, the best matching domain block for every range block should be searched. In the quantum scenario, the proximity between two states is measured from the quantum fidelity. In the Quantum based FIC, the best matching domain block for every range block is determined by maximizing their quantum fidelity, i.e.

$$\max[Tr(\sqrt{\rho_D}\rho_R\sqrt{\rho_D})^{\frac{1}{2}}]^2 \tag{4.7}$$

Where Tr(.) denotes matrix trace, ρ_D and ρ_R are density matrices of quantum states $|D\rangle$and $|R\rangle$, respectively.

Compression result is achieved by recording parameters of the search results, optimal affine scalar parameters, serial number of the best matching domain block, and serial number of the isometric operations.

4.1.1 Grover's Search Algorithm

The proposed Grover's algorithm performs a search over an unordered set of $N = 2^n$ items to find the unique element that satisfies some condition. While the best classical algorithm for a search over unordered data requires O(N) times, Grover's algorithm performs search on a quantum computer in only O(√N) operations, a quadratic speedup. In order to achieve such a speedup, Grover relies on the quantum superposition of states. This search principle is useful in reducing the search complexity in FIC to O(√N) steps. The algorithm steps are explained as in Fig. 2,

- Like many quantum algorithms, Grover's begins by putting the machine into an equal superposition of all possible 2^n states of the n-qubit register. Remember that means there is equal amplitude of $\frac{1}{\sqrt{2^n}}$ associated with every possible configuration of qubits in the system, and an equal probability of $\frac{1}{2^n}$ that the system will be in any of the 2^n states.
- The next series of transformations is often referred to as the Grover iteration and will be repeated √N times.

– The first step is rotating phases of all states by π if it is a desired state and by 0 otherwise.

– The next part of the iteration performs inversion about the average, transforming the amplitude of each state.

- Measure the resulting state.

The sequences of such operations would not be possible if the amplitudes did not hold that extra information regarding the phase of the state in addition to the probability. These amplitude amplification algorithms are unique to quantum computing because of this quality of amplitudes that has no analogue in classical probabilities.

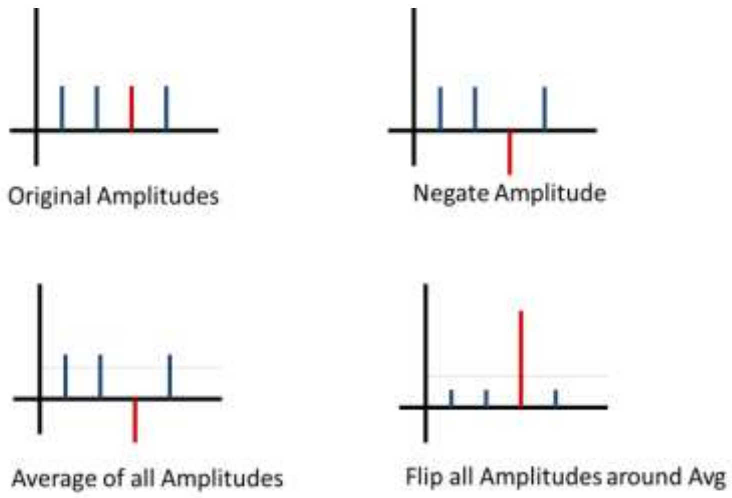

Figure.4.1 Algorithm Flow of Grover's Quantum Search

4.2 OPERATORS

4.2.1 Operator to Create Equal Superposition of States

An equal superposition of states is created by the application of the well-known Walsh-Hadamard operator [27]. The matrix representing the Walsh-Hadamard operator for an *n* bit quantum register is 2^n x 2^n matrix whose elements are defined to be: $W_{ij} = 2^{-n/2}(-1)^{i'.j'}$, where *i'* is the binary representation of *i*, and *i'.j'* is the bitwise dot product of the *n* bit strings *i* and *j*, *i* and *j* range from 0 to (N −1), Put another way, $W_{ij} = \pm 2^{-n/2}$, where the sign is positive if the bitwise AND of *i* and *j* has an even number of 1's and negative otherwise.

4.2.2 Operator to Rotate Phase

The matrix representing an arbitrary rotation operator is very simple. It takes the form of a diagonal matrix with $R_{ij} = 0$ if $i \neq j$, and $R_{ii} = e^{\sqrt{-1}\varphi_i}$. Here φ_i is an arbitrary real number, and from Euler's formula, the diagonal entries of the entries are equivalently written as $\cos\varphi_i + \sqrt{-1}\,\sin\varphi_i$.

4.2.3 Inversion about Average Operator

The inversion about average operation on state vector as an operator takes the amplitude of the i'th state, and increases or decreases it so that it is as much above or below the average as it was below or above the average before the operation.

The matrix representation of the inversion about average operator Â is defined: $A_{ij} = 2 / N$ if $i \neq j$ and $A_{ij} = -1+2 / N$. Note that $A = -I + 2P$ where I is the identity matrix, and P is the matrix with each element is equal to 1/N. Observe that P has the following two properties, first $P^2 = P$, and second P_v, for any vector ν, results in a vector ν' with each element being the arithmetic average of the elements of ν.

4.3 PARAMETERS USED FOR COMPARISON

Peak Signal to Noise Ratio (PSNR)

Peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale.

PSNR is most commonly used to measure the quality of reconstruction of lossy compression codecs (e.g., for image compression). The signal in this case is the original data, and the noise is the error introduced by compression. PSNR is given by:

$$PSNR = 20log\frac{Max_i}{\sqrt{MSE}}$$

Here Max_i is the maximum pixel value of the image.

Compression ratio (CR)

Compression ratio (CR) is a measure of the reduction of the detailed coefficient of the data. In the process of image compression, it is important to know how much detailed (important) coefficient one can discard from the input data in order to sanctuary critical information of the original data. Compression ratio can be expressed as:

$$CR = \frac{Decompressed\ Image}{Original\ Image}$$

Structural Similarity Index (SSIM):

The structural similarity (SSIM) index is a method for measuring the similarity between two images. The SSIM index is a full reference metric; in other words, the measuring of image quality based on an initial uncompressed or distortion-free image as reference. The difference with respect to other techniques mentioned previously such as MSE or PSNR is that these approaches estimate perceived errors; on the other hand, SSIM considers image degradation as perceived change in structural information. Structural information is the idea that the pixels have strong inter-dependencies especially when they are spatially close. These dependencies carry important information about the structure of the objects in the visual scene. The measure between two windows x and y of common size N x N is:

$$\text{SSIM} = \frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x{}^2+\mu_y{}^2+c_1)(\sigma_x{}^2+\sigma_y{}^2+c_2)}$$

With

- μ_x the average of x
- μ_y the average of y
- $\sigma_x{}^2$ the variance of x
- $\sigma_y{}^2$ the variance of y
- σ_{xy} the covariance of x and y
- c_1 and c_2 two variables to stabilize the division with weak denominator

Other parameters used for comparison are memory requirement and computation time. Memory requirement is calculated based on the image matrix size and search comparisons. The saving factor is determined based on the memory requirement comparison.

CHAPTER 5

SIMULATION RESULTS

This chapter compares the performance of the existing fractal image compression algorithms in literature over the proposed algorithm. The studied algorithms are applied on several types of images: natural images, textures, satellite images, benchmark images such that the performance of proposed algorithm can be verified for various applications. These benchmark images are the standard image generally used for the image processing applications. The results of the meticulous simulation for all images are presented in this section.

5.1 SIMULATION RESULTS

Two image sets, consisting of textures and satellite images, used to evaluate the performance of the proposed algorithm with the other algorithms are given in Figure.5.1 and Figure.5.2. The algorithms are simulated using Matlab R2012a on Intel(R) Core i5 2.5 GHz PC.

Figure.5.1 Texture image set

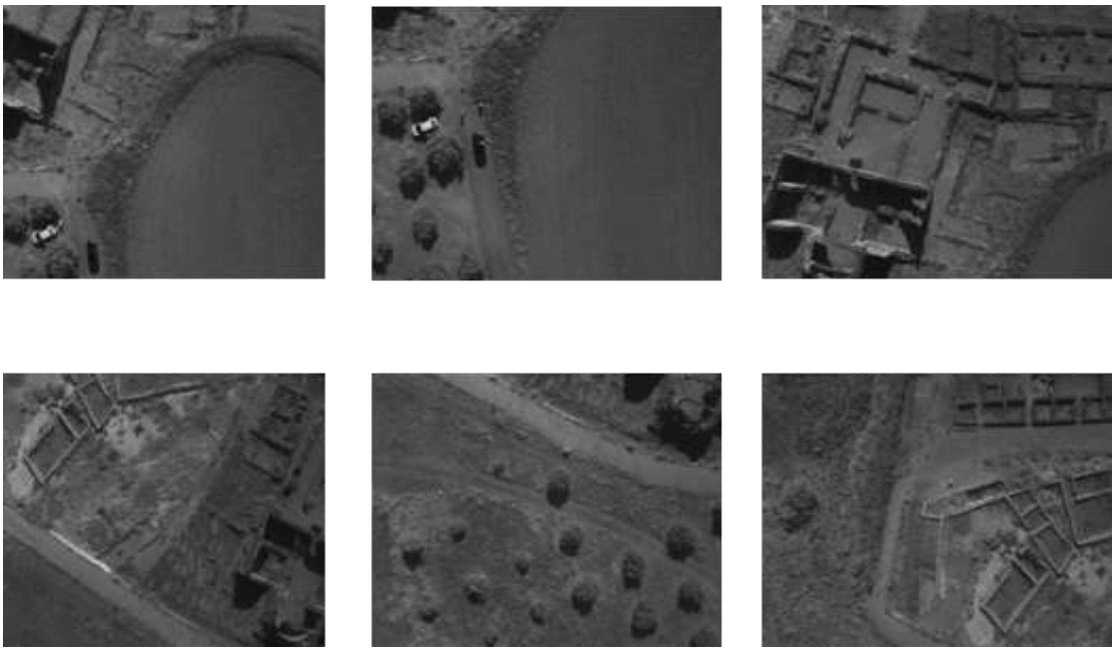

Figure.5.2 Satellite image set

The simulation results can be obtained for images of varying size. Original and reconstructed satellite images are shown in Figure.5.3. It can be seen, from Table.5.1, the compression ratio CR is high in satellite image for Quantum algorithm as compared to DCT, since this type of image is more based on fractal geometry. The decoded image quality measured as PSNR is good in quantum algorithm as there is no loss of detailed coefficients as in DCT.

Input Image Decoded-DCT Decoded-Quantum

PSNR= 38.716471 PSNR= 40.260905

PSNR= 38.481592 PSNR= 39.083457

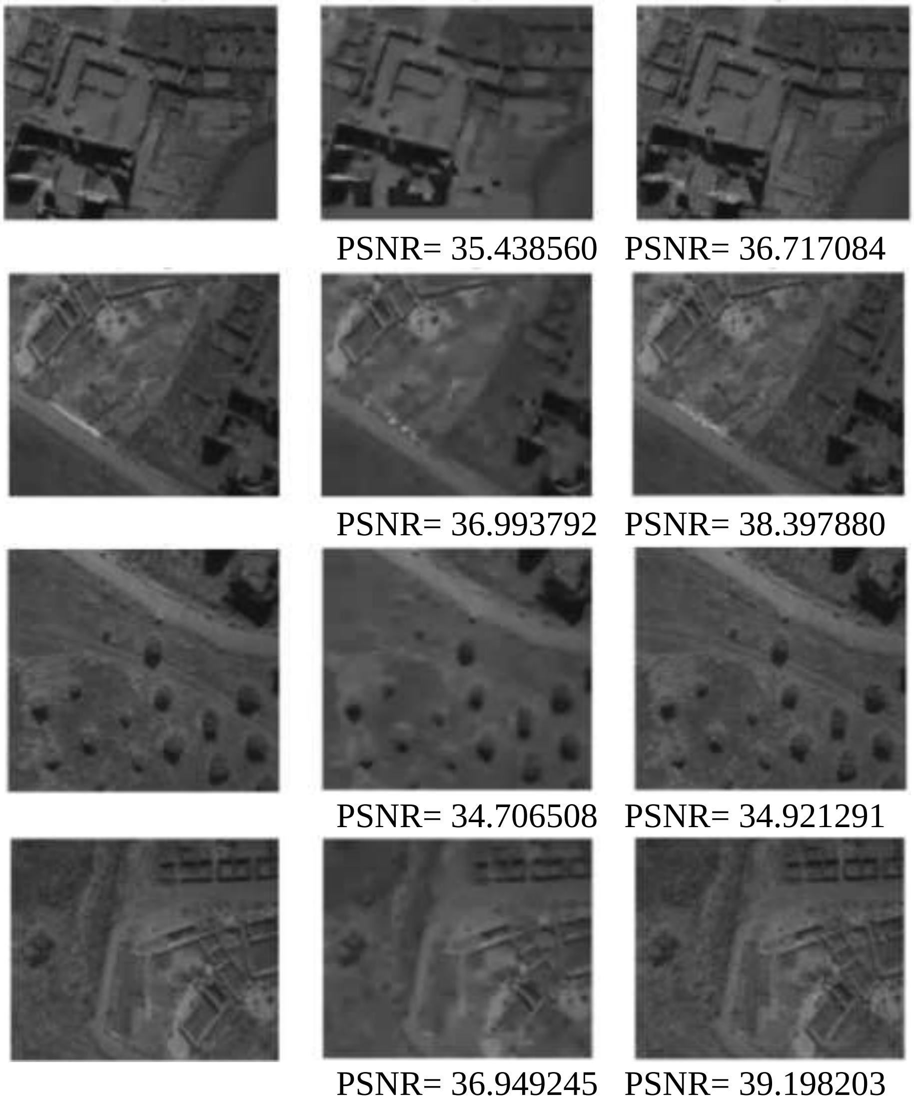

Figure.5.3 Original and Reconstructed Satellite images

Table.5.1 Performance comparison of existing and proposed algorithm

Input image	Compression factor		PSNR(dB)		Compression time(s)	
	DCT	QUANTUM	DCT	QUANTUM	DCT	QUANTUM
Satellite	24.93	28.53	35.43	36.71	9.45	3.35
Texture	19.57	19.12	32.13	37.9	11.42	1.17
Lena	11.79	8.86	34.32	37.13	7.69	1.20

Even though, DCT gives lesser compression ratio, it is computationally efficient compared to other traditional techniques. So, the comparison between quantum algorithm and existing computationally efficient DCT algorithm helps to understand the improvement of computational efficiency over the existing best algorithm. The results show that the required speedup is achieved in the proposed algorithm using quantum superposition of states. Especially for the fractal oriented satellite image, the compression time (CT) is reduced from 9.4 sec to 3.35 sec.

To increase the compression ratio further, the algorithm is run with different sizes of range and domain blocks. Smaller size of the block helps in identifying the most similar blocks which means a larger compressed file, because of more fractal codes. Figure.5.4 and Figure.5.5 gives the compressed images of single satellite and texture image respectively for two different block size. The performance results of quantum algorithm for texture and satellite images of two different block sizes are presented in the Table.5.2 and Table.5.3.

Input Image 16 x 16 Range block 8 x 8 Range block

PSNR= 34.30 dB PSNR= 36.87 dB

Figure.5.4 Original and Reconstructed Texture image from Quantum Algorithm

Input Image 16 x 16 Range block 8 x 8 Range block

PSNR= 39.198 dB PSNR= 39.240 dB

Figure.5.5 Original and Reconstructed Satellite image from Quantum Algorithm

Table.5.2. Performance comparison of quantum algorithm for Texture Image set

Input image	Compression factor		PSNR(dB)		Complexity(in Computations)	
Domain- Range -	32X32 16X16	16X16 8X8	32X32 16X16	16X16 8X8	32X32 16X16	16X16 8X8
Image 1	38.594	39.704	35.248	37.531	13010881	59534049
Image 2	37.904	38.618	34.370	35.932	13011137	59534305
Image 3	37.675	37.822	34.428	36.162	13010625	59533793
Image 4	38.102	38.826	34.244	36.043	13010753	59533921
Image 5	37.540	38.818	34.252	35.755	13011137	59534305
Image 6	37.672	39.108	34.301	36.878	13011009	59534177

Table.5.3.Performance comparison of quantum algorithm for Satellite Image set

Input image	Compression factor		PSNR(dB)		Complexity(in Computations)	
Domain- Range -	32X32 16X16	16X16 8X8	32X32 16X16	16X16 8X8	32X32 16X16	16X16 8X8
Image 1	39.458	40.289	40.260	39.316	13010881	59534049
Image 2	41.589	42.749	37.083	37.158	13011137	59534305
Image 3	28.533	30.721	36.717	36.850	13010625	59533793
Image 4	29.556	30.867	38.397	37.285	13010753	59533921
Image 5	39.724	42.411	34.291	32.572	13011137	59534305
Image 6	39.446	39.797	39.198	39.240	13011009	59534177

It is observed that from Figure.5.6 and Figure.5.7, the compression factor is improved in smaller block size without much degradation in the retrieved image quality. So when block size is reduced, the number of blocks to be searched is increased. Due to this the complexity of search is increased as shown in Figure.5.8. The complexity involved in two different sizes of the algorithm is given in the Table.5.4.

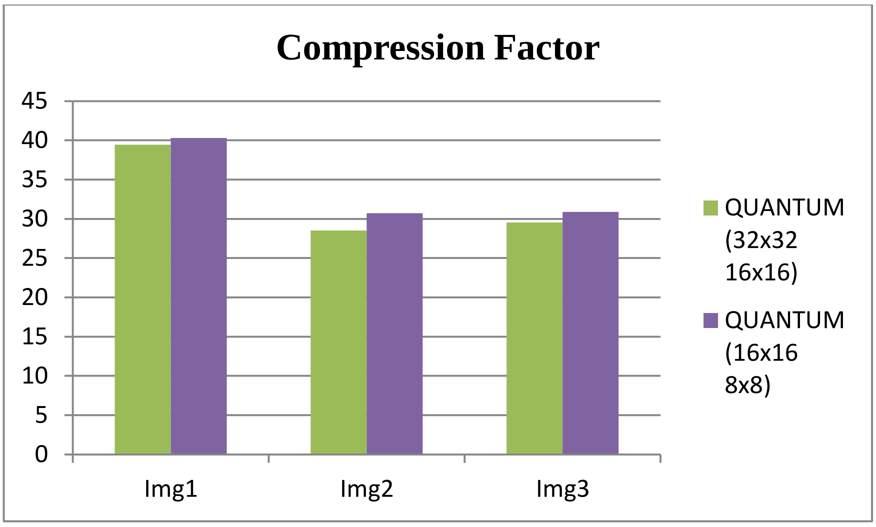

Figure.5.6 Comparison graph based on Compression factor for Satellite Images

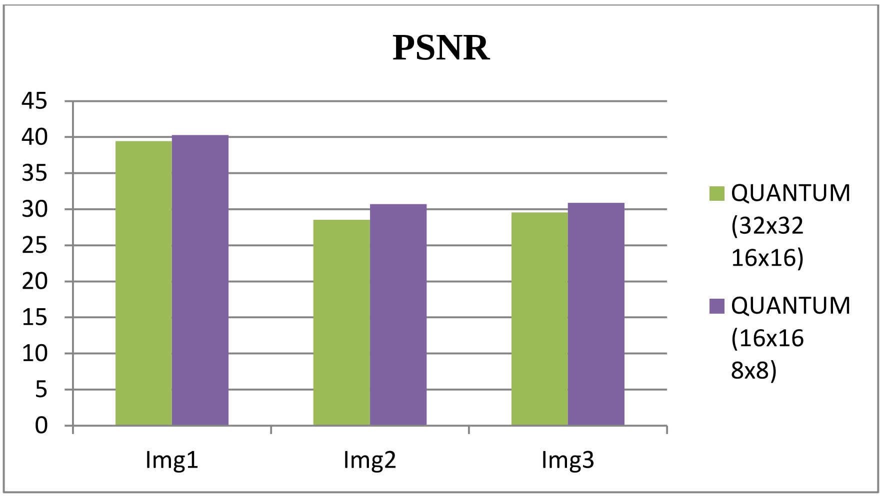

Figure.5.7 Comparison graph based on PSNR for Satellite Images

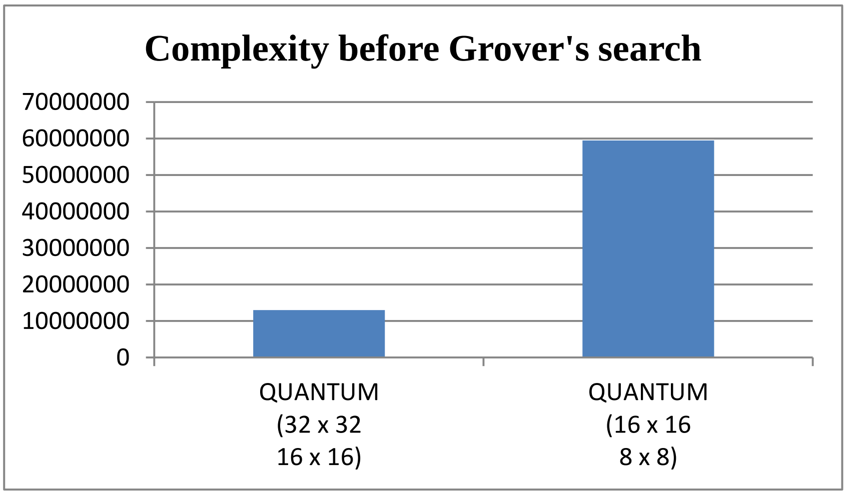

Figure.5.8 Comparison graph based on Complexity

Table.5.4 Complexity of Quantum algorithm for different sizes

Complexity	QUANTUM (32 X32 16X16)	QUANTUM (16X16 8X8)
In Quantum Representation	50881	59105
In Searching Similarities	12960000	59474944

Taken the size of the given input image is M x N, and the sizes of the domain blocks and range blocks are 2B x 2B and B x B, respectively. To represent all of the domain blocks and range blocks as quantum states, the computation required is (M – 2B + 1) x (N – 2B + 1) and (M/B) x (N/B) respectively. So the computational complexity of quantum representation should be O_{QR} = (M – 2B + 1) x (N – 2B + 1) + (M/B) x (N/B). Meanwhile, the computational complexity of searching self-similarities is O_{SS} = (M – 2B + 1) x (N – 2B + 1) x (M/B) x (N/B). Normally, the value of O_{QR} is several orders of magnitude smaller than the value of O_{SS}. For example, set M = N= 512 and B = 8, the ratio of O_{SS} to O_{QR} is 39870. Therefore, this gives every reason to neglect the computational complexity of quantum representation while calculating the computational complexity of the whole algorithm.

To reduce the search complexity specified in the Table.5.4, Grover's search is adopted along with the quantum FIC algorithm. This helps in reducing complexity to O(√N) steps. The Figure.5.9 depicts how Grover's search is deployed to search and code the single fractal part from the total blocks available.

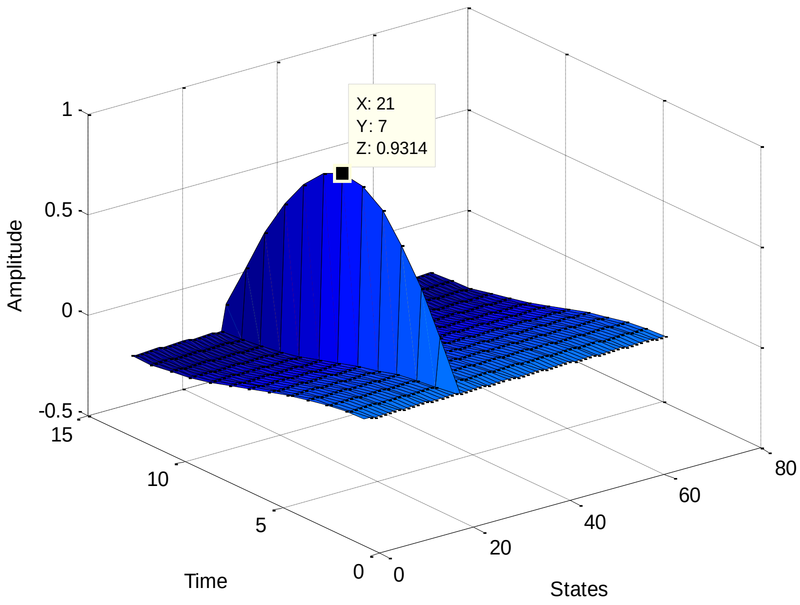

Figure.5.9 Grover's search of single fractal block

This is accomplished by observing the amplitudes of the resulting states in each step, it is identified that only the amplitude of the required state increases gradually at each step. Now when the system is observed, the probability that the state representative of the correct solution, measured in O(√N) is 93.14%. The probability of finding an incorrect state is 6.86%. Grover's algorithm is more likely to give the correct answer than an incorrect one with an input size of N = 64, and the error only decreases as the input size increases. Although Grover's algorithm is probabilistic, the error truly becomes negligible as N grows large.

Table.5.5 shows the amount of reduction in computations when the Grover's algorithm is adopted. The point at which we terminate Grover's algorithm and measure the result is critical. It has been shown that in Figure.5.10, the optimum number of Grover's iteration is $\approx \frac{\pi}{4}\sqrt{\frac{N}{M}}$, where M is the number of solutions.

Table.5.5 Complexity of Quantum algorithm with Grover's search for different sizes

Complexity	QUANTUM (32x32 16x16)	QUANTUM (16x16 8x8)
In Full search	12960000	59474944
In Grover's Search	3584	7680
In Grover's Search (Theoretical)	3600	7712

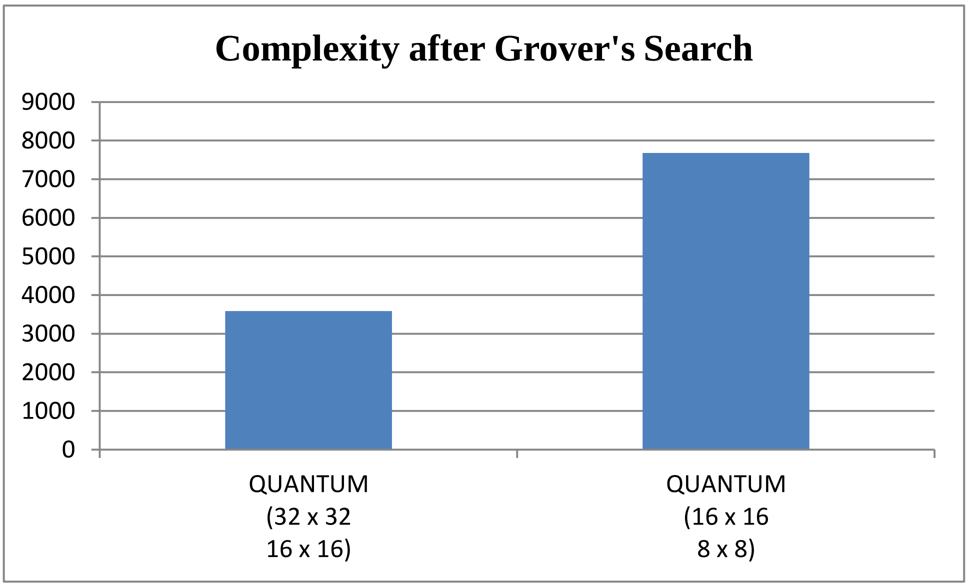

Figure.5.10 Comparison graph based on Complexity after Grover's search

CHAPTER 6

CONCLUSION AND FUTURE WORK

Quantum approach to fractal image compression has been examined and sought to improve it by formulating the search approach using Grover's algorithm. Experiment shows that the proposed representation on the algorithm without Grover's search can able to provide good compression factor and better reconstruction PSNR. Especially, for the images that consist of detailed view and structural similarities, performance of the algorithm is better. Hence, it can be implemented for compressing natural, texture and satellite images. In order to increase compression factor further, the simple modification to the algorithm like decreasing range and domain block size significantly had an impact on the compression results. But the search complexity in the algorithm remained as a drawback, because it results in high computational and time requirements of encoding part. Therefore, Grover's Search Algorithm has been adopted along with Quantum FIC, which resulted in a successful search with certainty in only $O\sqrt{N}$ attempts. Based on the comprehensive simulation results presented for different images, it can be seen that the Quantum-FIC algorithm along with Grover's search outperforms the existing algorithms.

As a future work different partitioning schemes and entropy encoding for the fractal codes can be implemented to further improve compression ratio.

REFERENCES

[1] R. Sudhakar, M.R. “Image compression using coding of wavelet Coefficients- a survey”, ICGST_GCCIP Journal, vol.5, no.6, pp. 25- 38, June 2005.

[2] C. Fu and Z. Zhu, “A DCT-based fractal image compression method”, in Proc. Int. Workshop Chaos-Fractals Theories and Applications (IWCFTA), pp. 439–443, Nov. 2009.

[3] R. E. Chaudhari and S. B. Dhok, “Wavelet transformed based fast fractal image compression”, in Proc. Int. Conf. Circuits, Systems, Communication and Information Technology Applications (CSCITA), pp. 65–69, Apr. 2014.

[4] Furao, Shen and Hasegawa, Osamu, “A fast no search fractal image coding method”, Journal of Signal Processing: Image Communication, vol.19, no.5, pp.393-404, Elsevier, 2004.

[5] Zhang, Yi and Wang, Xingyuan, “Fractal compression coding based on wavelet transform with diamond search”, Journal of Nonlinear Analysis: Real World Applications, vol.13, no.1, pp.106-112, Elsevier, 2012.

[6] Chen, Hsiu-Niang and Chung, Kuo-Liang and Hung, Jian-Er, “Novel fractal image encoding algorithm using normalized one-norm and kick-out condition”, Journal of Image and Vision Computing, vol.28, no.3, pp.518-525, Elsevier, 2010.

[7] Palazzari, Paolo and Coli, Moreno and Lulli, Guglielmo, “Massively parallel processing approach to fractal image compression with near-optimal coefficient quantization”, Journal of systems architecture, vol.45, no.10, pp.765-779, Elsevier, 1999.

[8] Md. Enamul Haque, Abdullah Al Kaisan, Mahmudur R. Saniat, Aminur Rahman, “GPU Accelerated Fractal Image Compression for Medical Imaging in Parallel Computing Platform”, Journal of CORR, vol. abs/1404.0774, 2014.

[9] Chauhan, Munesh Singh and Negi, Ashish and Rana, Prashant Singh, “Fractal image compression using dynamically pipelined GPU clusters”, Proceedings of the

Second International Conference on Soft Computing for Problem Solving (SocProS 2012), pp.575-581, Dec 2012.

[10] Yung- Ching Chang, Bin-Kai Shyu,Jia- Shung Wang, “ Region Based fractal compression for still image”, 2010.

[11] Suman K. Mitra, C. A. Murthy, and Malay K. Kundu, “Technique for Fractal Image Compression using Genetic Algorithm”, IEEE Transaction On Image Processing, vol. 7, NO. 4, Apr 1998.

[12] D. Karaboga, “An idea based on honey bee swarm for numerical optimization”, Tech. Report TR06, Erciyes University, Engineering, Faculty, Computer Engineering Department, 2005.

[13] Wang, Jianji and Zheng, Nanning, “A novel fractal image compression scheme with block classification and sorting based on Pearson's correlation coefficient”, IEEE Transactions on Image Processing, vol.22, no.9, pp.3690-3702, Proc. IEEE, 2013.

[14] Hassaballah, Makky and Mahdy, Youssef B and Makky, MM, “A fast fractal image compression method based entropy”, in ELCVIA: electronic letters on computer vision and image analysis, vol.5, pp.30-40, 2005.

[15] Kamel Belloulata and Janusz Konrad, “Fractal Image Compression with Region-Based Functionality”, IEEE Trans. Image Process, vol. 11, no. 4, pp. 351-362, Apr. 2002.

[16] Wang, Hai, “Fast image fractal compression with graph-based image segmentation algorithm”, International Journal of Graphics, vol.1, no.1, pp.19-28, 2010.

[17] R.Distasi, m.Nappi, and d. Riccio, “Range/domain approximation error-based approach for fractal image compression”, IEEE trans. Image processing vol. 15, no. 1, pp.89–97, Jan. 2006.

[18] Kung, CM and Yang, WS and Ku, CC and Wang, CY “Fast fractal image compression base on block property”, In IEEE 2008 International Conference on Advanced Computer Theory and Engineering, Phuket, pp.477-481, Dec. 2008.

[19] S.E. Venegas-Andraca and S. Bose, “Storing, Processing, and Retrieving an Image using Quantum Mechanics”, in Proc. of SPIE Conf. Quantum Information and Computation, pp.137-147, 2003.

[20] S. Yuan, X. Mao, Y. Xue, L. Chen, Q. Xiong and A. Compare, “SQR: a simple quantum representation of infrared images”, Quantum Inf. Process., vol. 13, no. 6, pp. 1353-1379, 2014.

[21] H.-S. Li, Z. Qingxin, S. Lan, C.-Y. Shen, R. Zhou and J. Mo, “Image storage, retrieval, compression and segmentation in a quantum system”, Quantum Inf. Process., vol. 12, pp. 2269-2290, 2013.

[22] H.S. Li, Q. Zhu, R.G. Zhou, L. Song and X.J. Yang, “Multi-dimensional color image storage and retrieval for a normal arbitrary quantum superposition state”, Quantum Inf. Process., vol. 13, no. 4, pp. 991-1011, 2014.

[23] H.S. Li, Q. Zhu, R.G. Zhou, M.C. Li, I. Song and H. Ian, “Multidimensional color image storage, retrieval, and compression based on quantum amplitudes and phases”, Inf. Sci., vol. 273, pp. 212-232, 2014.

[24] S.E. Venegas-Andraca and J.L. Ball, “Storing Images in engtangled quantum systems”, Quantum Inf. Process., vol. 9, pp. 1-11, 2010.

[25] J.I. Latorre, “Image compression and entanglement”, arXiv:quantph/ 0510031 (2005).

[26] P. Le, A. Iliyasu, F. Dong and K. Hirota, “A flexible representation and invertible transformations for images on quantum computers”, in New Advances in Intelligent Signal Processing, Springer, Berlin, vol. 372, pp. 179-202, 2011.

[27] P.Q. Le, F. Dong and K. Hirota, “A flexible representation of quantum images for polynomial preparation, image compression, and processing operations”, Quantum Inf. Process., vol. 10, pp. 63-84, 2010.

[28] B. Sun, P.Q. Le and A.M. Iliyasu, “A multi-channel representation for images on quantum computers using the RGB color Space”, in Proc. of the IEEE 7th Int. Symp. on Intelligent, Signal Process., pp. 160-165, 2011.

[29] Y. Zhang, K. Lu, Y. Gao and M. Wang, "NEQR: a novel enhanced quantum representation of digital images", Quantum Inf. Process., DOI 10.1007/s11128-013-0567-z.

[30] A. Klappenecker and M. Rotteler, "Discrete cosine transforms on quantum computers", in Proc. IEEER8-EURASIP Symp. on Image and Signal Processing and Analysis, Croatia, pp. 464-468, 2001.

[31] C.C. Tseng and T.M. Hwang, "Quantum circuit design of 8 x8 discrete cosine transforms using its fast computation flow graph", in Proc. IEEE Int. Symp. on Circuits and Syst., Japan, vol. 1, pp. 828-831, 2005.

[32] A. Fijany and C.P. Williams, "Quantum wavelet transform: fast algorithm and complete circuits", arXiv:quant-ph/9809004,1998.

[33] B. Sun, A. Iliyasu, F. Yan, F. Dong and K. Hirota, "An RGB multichannel representation for images on quantum computers", J. Adv. Comput. Intell. Intell. Inform., vol. 17, no. 3, pp. 404-417, 2013.

[34] S. Caraiman and V. Manta, "Image processing using quantum computing", in System Theory, Control and Computing (ICSTCC), pp. 16, Oct. 2012.

[35] Y. Zhang, K. Lu, Y. Gao and K. Xu, "A novel quantum representation for log-polar images", Quantum Inf. Process., vol. 12, pp. 3103-3126, 2013.

[36] S. Caraiman and V. Manta, "Histogram-based segmentation of quantum images", Theor. Comput. Sci., vol. 529, pp.46-60, 2014.

[37] S. Caraiman and V.I. Manta, "Image segmentation on a quantum computer", Quantum Inf. Process., vol. 14, pp. 1693-1715, 2015.

[38] P.Q. Le, A.M. Iliyasu, F. Dong and K. Hirota, "Strategies for designing geometric transformations on quantum images", Theor. Comput. Sci., vol. 412, pp. 1406-1418, 2011.

[39] P.Q. Le, A.M. Iliyasu, F. Dong and K. Hirota, "Efficient color transformations on quantum images", J. Advanced Computational Intell. And Intelligent Informatics, vol. 15, pp. 698-706, 2011.

[40] F. Yan, P.Q. Le, A.M. Iliyasu, B. Sun, J.A. Garcia, F. Dong, and K. Hirota, "Assessing the similarity of quantum images based on probability measurements", in 2012 IEEE Congress on Evolutionary Computation (CEC), pp. 1-6, June 2012.

[41] R.-G. Zhou, Q. Wu, M.-Q. Zhang and C.-Y. Shen, "Quantum image encryption and decryption algorithms based on quantum image geometric transformations", Int. J. Theor. Phys., vol. 52, no. 6, pp. 1802-1817, 2013.

[42] A.M. Iliyasu, P.Q. Le, F. Dong and K. Hirota, "Watermarking and authentication of quantum images based on restricted geometr c transformations", Inf. Sci., vol. 186, no. 1, pp. 126-149, 2012.

[43] A.M. Iliyasu, P.Q. Le, F. Yan, B. Sun, J.A.S. Garcia, F. Dong and K. Hirota, "A two-tier scheme for greyscale quantum image watermarking and recovery", Int. J. Innov. Comput. Appl., vol. 5, pp. 85-101, 2013.

[44] W.-W. Zhang, F. Gao, B. Liu, H.-Y. Jia, Q.-Y. Wen and H. Chen, "A watermark strategy for quantum images based on quantum Fourier transform", Quantum Inf. Process., vol. 12, pp. 793-803, 2013.

[45] W.-W. Zhang, F. Gao, B. Liu, H.-Y. Jia, Q.-Y. Wen and H. Chen, "A quantum watermark protocol", Int. J. Theor. Phys., vol. 52, no. 2, pp. 504-513, 2013.

[46] S. Caraiman and V. Manta, "Quantum image ltering in the frequency domain", Adv. Electr. Comput. Eng., vol. 13, no. 3, pp. 77-84, 2013.

[47] Y. Zhang, K. Lu, Y.-H. Gao, and M. Wang, "A quantum algorithm of constructing image histogram", World Acad. Sci. Eng. Technol., vol. 7, no. 5, pp. 610-613, 2013.

[48] S. Caraiman and V. Manta, "Image representation and processing using ternary quantum computing", in Adaptive and Natural Computing Algorithms, Springer, Berlin, vol. 7824, pp. 366-375, 2013.

[49] A.M. Iliyasu, "Towards Secure and Efficient Image and Video Processing Applications on Quantum Computers", Entropy, vol. 15, no. 8, pp. 2874- 2974, Jul. 2013.

LIST OF PUBLICATIONS

- Presented a paper titled "Fractal Image Compression using Quantum Algorithm" in **IEEE sponsored 3rd International Conference on Innovations in Information, Embedded and Communication Systems** on 17th and 18th March 2016 at Karpagam college of Engineering, Coimbatore.
- The paper is accepted to be published in a Scopus Indexed (Anna University Annexure-II) Journal, **Pakistan Journal of Biotechnology** (S.No: 15755, Print ISSN: 18121837, University of Sindh).