Matrix Data Optimization Technique Applied to Bi-Faceted Binary Images for the Purpose of Modernization

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Abstract

Picture reconstruction is a process that involves reassembling image data using the parcel data that was provided as input. The horizontal projection, the vertical projections, both the horizontal and vertical projections, the diagonal projection, and the anti-diagonal projection data might all be included in the partial input data. Picture reconstruction techniques are put to use in order to piece together fragments of data that have been lost entirely or information that has been distorted based on the remnants of the image data. The binary image matrices are built up of the 1-bit image pixels, which only have two possible pairings and may store either the value 1 or 0. Binary pictures are sometimes known as black and white images since two-bit images can only display either black or white, which is represented as a value of either one or zero in binary image matrices. Several binary image reconstruction approaches have previously been developed for the reform of binary images starting from some type of input traces or the projection data. These methods may be used to recreate the whole binary matrix. When either the maximum number of iterations is reached or the horizontal and vertical combination difference equals zero during the process of reconstructing an image, the initial image reconstruction solution is returned. This is accomplished by making an estimate of the binary combinations that are produced by the proposed model solution. The genetic programming was used in the second stage of the image matrix reconstruction, which utilized the primary phases of image reconstruction based upon the genetic reproduction. These primary phases of image reconstruction include crossover, mutation, and fitness for the finalization of the binary image matrix reconstruction solution. The genetic programming was used in the second stage of the image matrix reconstruction. A binary picture may be reconstructed using a variety of different kinds of experiments, which are currently being carried out. In order to accomplish this goal, examination of the suggested model is now taking place with monitoring of their performance. The suggested model has been validated by putting it through its paces using binary image matrices of varying sizes, which includes the (10x10, 20x20, 30x30, 40x40, 50x50, 60x60, 70x70, 80x80, 90x90 and 100x100 sizes). The suggested model has been shown to record a higher level of reconstruction accuracy, which can be seen in the form of the reconstruction error. In addition, the time-consuming nature of the process has been analyzed as part of the comparison of the proposed model to the current models. In the research, the accuracy of picture reconstruction is discussed in relation to the suggested model, which, in comparison to the current model, has attained a good position.

1. The Beginning of the Image Reconstruction Process

Picture reconstruction is used as the foundation for the introduction of this article, which goes on to detail the method by which image data may be replicated back by image traces [1]. The projection is the form that allows traces of the picture data to be retrieved in a range of dimensions, and it may be used in many different situations. The use of image data is likely to be of assistance in obtaining projections in the horizontal, vertical, and diagonal planes. [2] Depending on the kind of pictures, the projection data include a tally of rows and columns that are either in two dimensions or three dimensions respectively. The study makes use of 1-bit binary pictures, which can only be combined in two ways: either 1 or 0. These images are only ever utilized in these two states. The reform of binary images is dependent on the first solution, which computes the preliminary combination and ensures that the projection data will be satisfied. Utilizing projection data to re-create the projected binary pictures inside an interactive setting while simultaneously running the program itself. It came into being after the computation of a number of different combinations to produce basic picture matrices. Matrix optimization is accomplished by feeding the matrix result that has been acquired from an initial solution into a genetic algorithm in order to achieve the desired result. This is because the projection data that was provided included the best possible combination of an optimum solution for this G A will be liable for it. In the course of conducting this research, a wide range of factors will be taken into consideration in order to conduct an analysis of the outcome and performance score of the proposed model. The reconstruction accuracy, precision, peak signal-to-noise ratio, amount of time that has passed, and computational complexity are the parameters that are employed. As can be seen in the following diagram, the development of interactive picture reconstruction algorithms will include a total of 5 different components:

[1] An object model that describes the unknown continuous-space function that is to be rebuilt in terms of a finite series with unknown coefficients that must be estimated from the data. This function is to be reconstructed in order to provide an answer to a question.

[2] A model of the system that establishes a relationship between the unknown item and the "ideal" measurements that would be obtained if there were no measurement noise present. Most of the time, this is represented by a linear model in the form, where stands for the noise.

[3] A statistical model that depicts how the noisy data fluctuate around their ideal values and how these values are determined. The Guassian noise or poison statistics are often assumed. It is more common to utilize Poisson statistics since they are more reflective of the actual world.

[4] A cost function that has to have its value reduced so that the image coefficient vector may

be estimated. A regularization of some kind is often included into this cost function. On occasion, the regularization will be derived from Markov random fields.

[5] An approach, which is often iterative, for reducing the cost function, which includes some kind of starting estimate of the picture and some sort of stopping condition for ending the iterations. [6] A method for maximizing the value of the cost function.

It is also possible to show the picture as a two-dimensional function, as follows:

The x and y coordinates are being utilized for this purpose here. On each given set of coordinates, the intensity of the picture, denoted by the letter I, or its gray value, denoted by the letter f, is referred to as the amplitude (X, Y). All of the values of the spatial coordinator as well as the amplitude are examples of discrete, finite quantities that are together referred to as a digital picture.

The processing of digital images may subsequently be segmented into a number of different portions depending on the following methods:

Images serve both as inputs and outputs of the system.

There is a possibility that photographs may be used as input, and if there is output, it will be an attribute retrieved from the images themselves.

An assortment of noises, such as Gaussian noise, speckle noise, salt and pepper noise, and shot noise, are included into the formation of the picture. Filtering is the most effective method for removing noise from a picture. Now let's speak about filters that may be used for noise reduction. The picture has a variety of filters, including the median filter, the average filter, the wiener filter, and many more. Because of the losses that occur in it, the picture that is produced is one in which it is either excessively smooth or blurry to an extreme degree.

1.1 The Processing of Images in Color

The human visual system is capable of differentiating between tens of thousands of hues and intensities over hundreds of thousands of color variations. And there are only one hundred different colors of grey to choose from. In order to depict the specific hue, we employ three different quantities that are completely independent of one another. It is the major wavelength through which hue is determined in the electromagnetic spectrum, and if it is seen where the visible colors come from, it sits between 400 mm (violet) and 700 mm. If it is seen where the colors originate from, it is seen where the hue is decided (red).

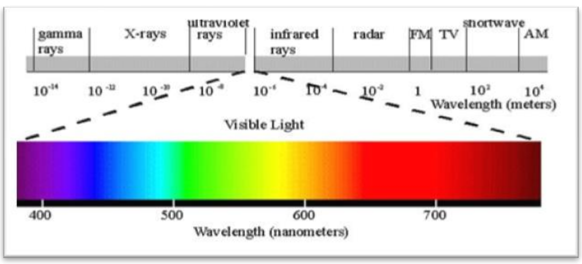

Figure 1.1 visible spectrum chart

Purity of the excitation the amount by which the white light is altered with hue is one technique to determine the degree to which the color is saturated. When we talk about a color that is pure, we imply that it is totally saturated, which also indicates that there is no white light mingled into it. The chromaticity may be mutually determined based on the provided colors, hue, and the context. Last but not least, the intensity is established with the assistance of the real quantity of light, with lighter colors correlating to colors with a higher intensity.

1.2 Colour Perception

There are three different kinds of cones found in the human retina. The response of each different kind of cone as a function of the wavelength of the light that is impressed onto it. The highest point of each and every curve is located at 440 nm (for blue), 545 nm (for green), and 580 nm (red).

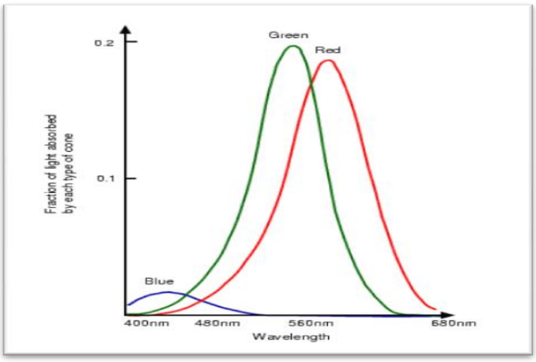

Figure 1.2. Peaks for each curve at 440nm (blue), 545nm (green), and 580nm (red).

1.3 Variations in the Coloration of the Models

There are established protocols for articulating certain hues via the use of color models. Which may be comprehended using the three-dimensional coordinate system and the subspace, each of which provides a specific model for the various constructive colors? Any color may be chosen to represent a model, and that model's only point of contact inside the subspace will be with a single point. Each color model is in some way focused on either the particular hardware being used (RGB, CMY, or YIQ), or the image processing program that is being used (HSI).

1.4 The Red Green Blue Model

Every picture in the RGB model consists of three different image planes that are independent from one another. Each Comes in a Singular Primary Color Option. When we talk about the fundamental colors, we're talking about red, green, and blue. Now, if each hue needs to be given, it is essential to indicate the quantity of main components that are present.

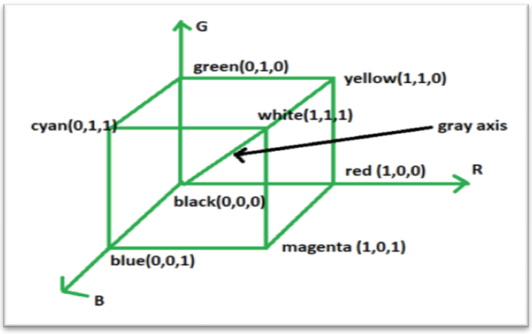

Figure 1.3 The grayscale spectrum lies on the line joining the black and white vertices.

1.5 The Color Model Using CMYK

The cyan-magenta-yellow model, sometimes known as the CMY model, is a subtractive model that is appropriate for the absorption of color. An illustration of this would be the pigments that are found in the paints. A connection between the RGB model and the CMY model is shown below, and it is as follows:

$$\begin{bmatrix} C \\ M \\ Y \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} - \begin{bmatrix} R \\ G \\ B \end{bmatrix}.$$

Figure 1.4 illustrates the result of blending three secondary colors together. It is produced by combining the world's three main hues, which are red, green, and blue.

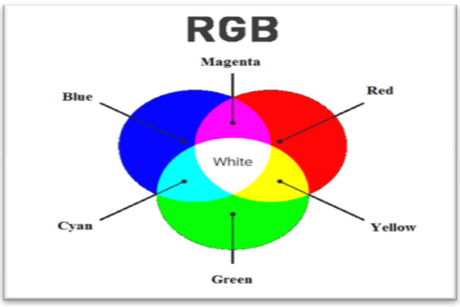

Figure1.4 RGB color model

When you combine red and green, you get the color yellow. When you combine blue and green, you get the color cyan. To get the color white, combine equal parts of the colors red, green, and blue. Finally, mix equal parts of the colors red and blue to produce the color magenta. Secondary colors are produced by similar mixing processes. It is broken down into its simplest form below.

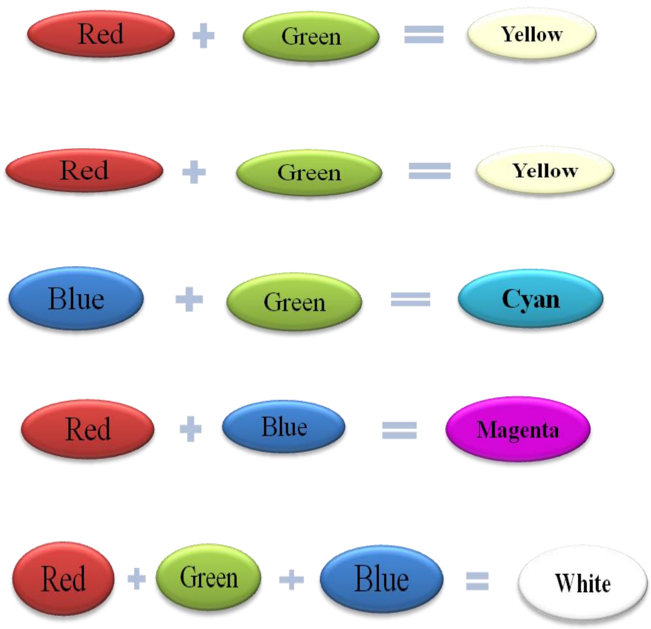

Figure 1.5 CMYK color model

The CMY model is used by printing equipment as well as filters. Figure 1.5 depicts three subtractive primaries together with their pair-wise combinations, which explain how the colors red, green, and blue may be obtained. Lastly, in order to create the color white, the color black will need to be subtracted from each of the three basic colors.

In printing machines and filtering systems, the CMY model is used. Figure 1.5 depicts three subtractive primaries and the pair-wise combinations that may be used to recover the colors red, green, and blue. Furthermore, in order to achieve the color white, the color black will need to be subtracted from each of the three main colors.

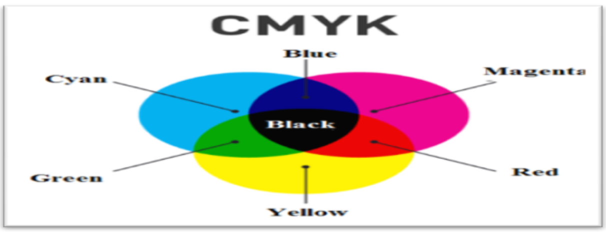

Figure 1.5 CMYK color model

2FORMULATION OF THE PROBLEM..

In this study article, image reconstruction has been suggested over the binary pictures in the multi-level reconstruction. The horizontal and vertical (HV) projections serve as the foundation for the binary image reconstruction that is performed in this study. The pictures that include the multidimensional binary forms in the binary matrix are what are referred to as the HV-convex images. Reconstructing binary-based feature descriptor data, direct binary image captures, and OCR text extraction pictures may all benefit from the image reconstruction technique. The difficulty of recovering binary data from horizontal and vertical projections is the primary focus of the model that has been offered as a solution to the problem.

2.1 RESEARCH OBJECTIVES

i. To create and assess the suggested model design in order to overcome the limitations of the current models.

ii. To put into action the production of the first solution, complete with double-cross assessment based on segmentation.

iii. In order to implement and troubleshoot the suggested model, the MATLAB simulator must be employed.

iv. To get the outcomes from the suggested model design and conduct an analysis of them.

v. In order to narrow down the options, the picture de-noising filters' overall effectiveness will be evaluated.

vi. To determine the inadequacies of the picture de-noising filters that are currently in use

vii. To create a better algorithm for the median filter or a hybrid picture de-noising filter

viii. To carry out the implementation of the newly devised enhanced median filter algorithm or hybridized image de-noising filter

ix. In the direction of the acquisition of results of the recently suggested image de-noising filter

2.2 FORMULATION

The picture rebuilding solution generating model that is offered in this research was developed utilizing double-level (Optimization problems 1 and 2) and the simulated annealing method. This was done in order to generate the model that is presented. The simulated annealing algorithm is based on the concept of metallurgy, in which a process is used to a metal or glass to progressively cool it in order to eliminate internal tension and toughen the metal or glass. This concept was inherited by the simulated annealing algorithm. Annealing produces the highest possible strength in the metal or glass while maintaining the necessary flexibility. The solution is thus employed over the HV-convex image regeneration, where it has been utilized to tackle the issue of 2-D binary matrix reconstruction in order to build a reliable solution for image reconstruction. This was done in order to develop a resilient solution for image reconstruction. However, it is possible that simulated annealing will not function as the appropriate solution over the binary image matrix. This is due to the fact that there is a relatively high probability of creating the error during the process of image reconstruction, as defined in the results of the existing scheme. When used in a layered form, the solutions for Optimization Problems 1 and 2 could interfere with each other and cause more complications. A single approach for the production of robust initial solutions will provide solutions that are both more accurate and more resilient.

There are several distinct kinds of sounds that may be created in the visual data. The most renowned picture noises include Amplifier noise (Gaussian noise), Salt-and-pepper noise, Shot noise (Poisson noise), and Speckle noise. The research presented in this article has an emphasis on properly removing salt and paper from a picture without causing a decrease in its overall quality.

If I conceal the detail that is already in the picture, it has a significant influence on the image, and it also affects the clarity of the photographs. This is because it causes the image to become less clear. The majority of the time, we encounter salt and paper noise during the transmission of the file. The total number of values that may be assigned to this noise is one of two numbers: 0 or 1. Each possible outcome has a probability that is lower than 0: 1. During the digitization process, timing mistakes, malfunctioning of pixel components in the camera sensors, and faulty memory locations are common causes of this noise. Additionally, this noise may also be caused by defective memory locations.

3. DESIGN AND IMPLEMENTATION

In most cases, the number of possible outcomes for the reconstruction problem is quite high [99]. Thus to reach an answer one needs certain limitations. do not supply a single solution, which makes it reasonable to choose the best solution (with respect to some pre-defined optimality criteria, according to the application area).

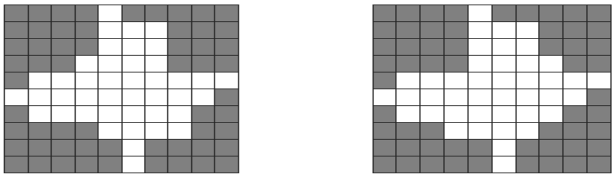

Figure 3.1: Two different HV- convex images with the same projection set

In order to narrow down the search space, we will be using the convexity constraint in this chapter. The class of HV convex binary images has been taken into consideration, and the projection set with only two orthogonal directions—namely, the horizontal direction (1, 0) and the vertical direction (0, 1)—has been taken as the solution space for a given set of projections. This set of projections is the only one that has been used. Therefore, the projections are set to,, and respectively. The HV convexity with projections from two different directions does not offer a distinctive answer [12].

The class of h-v convex matrices with specified projections in two directions and is quite big in real applications, which makes it hard to discover the correct solution [64]. In addition, there are many instances in which the precise answer is not necessary (for instance, it may add instrumentation inaccuracy in projections to the solution), and as a result, the most advantageous way out is the sought for solution in situations when issues arise. Because the class is large and the optimization criteria are dependent on only projection data and a-priori information, typical optimization methods might not work very well. As a result, we use a stochastic optimization technique (minimization algorithm) that is derived from thermodynamics and is known as genetic programming [129,149]. In section 3.2, we will give a brief description of the Genetic programming approach. In section 3.3, the analog of Genetic programming in discrete tomography is described. In section 3.4, a brief description of the boundary point and envelop point is given. In section 3.5, the proposed reconstruction algorithm that is based on the Genetic programming approach is given. In section 3.6, the implementation of the proposed reconstruction algorithms is given. In section 3.7, the investigational results of the proposed algorithm are presented.

3.1 GENETIC PROGRAMMING

The term "global optimization algorithm" refers to genetic programming, which belongs to the same class as stochastic optimization algorithms and Meta-Heuristic algorithms. The optimization of functions may be accomplished via the use of genetic programming, which is a modification of biological chromosomal selection. This strategy provides a foundation upon which a wide range of expansions and specifications of the basic technique may be built.

In natural creation, the process of selection in genetics encourages genetic programming. Genetics are involved in creation. This natural process of the gene hypothesis is related with the development of the genome in biological entities such as humans and other organisms. During this stage, chromosomal sets consisting of 23 chromosomes are acquired from both the female and male components. These sets then go through the process of selection to choose which 23 chromosomes will be used to create the new population.

3.2 GENETIC PROGRAMMING APPROACH IN DISCRETE TOMOGRAPHY

The physical process of offspring generation is an analogy that, when applied to biological things, takes on a significance that is highly vital for the survival of the genes. The projected model has been provided to construct the picture by using a method that is analogous to biological offspring production in order to bring the process of population generation via gene theory to a successful conclusion.

This is represented as each image having a given projection set, and either some a-prior information or some a-prior information must also be satisfied. The chromosomes are the system's state variables, and the goal of the system is to arrive at genetic equilibrium under the best possible biological conditions and situations. By using a slow cooling method, the system's optimization may be accomplished in the fewest number of rotations or iterations, which results in the lowest possible cost (fitness) function. To put it another way, a strategy that is based on genetic programming may be characterized as:

Define the class of feasible solutions for the given projection set and restrictions; this class will be the search space. The new generation production process says that the values of can be interchanged such that (selection of optimal chromosomes), and the cooling will say to find such that lowers the energy (cost/ fitness function) by selecting the optimal pairs ought to reach an optimal or near-optimal solution. Each element F of the search space is a binary image containing (mn) values (pixels/cells), which are conditions (variables).

In this genetic programming procedure, the selection of chromosomes is treated as a switching operation. The switching operation itself is treated as a free movement, and this free movement has been taken into consideration in this thesis in order to make binary bit decisions based on the environmental conditions or variables calculated throughout the various iterations. Because the number of pixels (cells) on the boundary of the image is a smaller amount than the number of pixels (cells) in the entire image, the switching is only done at the boundary of the image in the current work. Since this will speed up the overall process, the switching is only done at the boundary of the image.

3.3 ADJACENT POINTS, BOUNDARY POINTS, AND ENVELOP POINTS

In this section, some definition is given that explain the movement of chromosomes in the Genetic programming process.

3.3.1 Adjacent cells and adjacent points

Any two cells (i,j) and (i',j') in X is said to be adjacent if either $i = i'$ and $|j - j'| = 1$ or $|i - i'| = 1$ and $j = j'$. **3.3.2 Adjacent points of a binary image or connected image**

If $f_{ij} = F(X(i,j))$ and $f_{i'j'} = F(X(i',j'))$ both have value 1 and cells (i,j), and (i',j') are adjacent then these points of binary image are said to be connected. If all the points of binary image F are connected then it is called connected image.

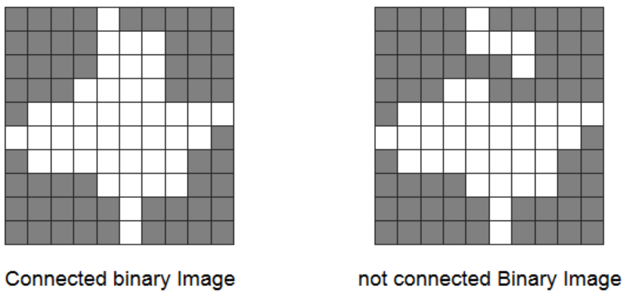

Figure 3.2: Connected binary image and not connected binary image

3.3.3 Boundary of a binary image

The binary image F says that it contains 1's at some cell (i, j) and 0's at other cells in the discrete set X, hereafter by an image we will refer the cells having a value of F as 1 i.e $F(X(i,j)) = f_{ij} = 1$ and the cell or point (I,j) of X will be said to be a point of binary image F, i.e. $f_{ij} = 1 \Rightarrow (i,j) \in F$.

The set of all cells (points) (i, j) in F which separate 1's from 0's will be called the boundary of$F$, thus the boundary of F is represented as

$$B_F = \{(i,j) \in F : \exists \; adjacent \; point \; (i',j') \notin F\} \qquad (3.1)$$

Similarly, the boundary is defined in [202].

3.4 RECONSTRUCTION ALGORITHM BASED ON GENETIC PROGRAMMING

Our reconstruction problem $(F_{hv}, \mathcal{P})$ $\mathcal{P} = P(R, C)$ has been transformed into an optimization problem

$$\max\ (n_{hw}) \qquad (3.13)$$

Subject to

$$\sum_{i=1}^{m} f_{ii} = c_i \quad \forall j = 1(1)n \qquad (3.2$$

The proposed reconstruction algorithm based on Genetic programming approach:

3.4.1 Initial solution

Any fundamental reconstruction approach may be used to acquire the first solution of the reconstruction problem; however, this technique does not provide the desired convex picture.

3.4.2 Image regeneration process

The boundary point switching procedure has traditionally been seen to include the free selection of chromosomes; hence, the chromosomes themselves are understood to constitute components of the boundary point switching process. As the probability decreases, the fitness can be controlled by adjusting the assignment of the probability that boundary point switching components will be selected for switching operation. The highest probability serves as the starting point, and it is also the point at which all of the switching components for the boundary points have an equal chance of being selected. The probabilities that have been assigned to these switching components have been determined in accordance with the category of boundary points and envelop points that, when considered together, make up the switching component. In our approach, a boundary point switching component has been given a larger value if there is a greater likelihood of improvement in a measure of convexity. This is because there is a correlation between the two factors. Therefore, during a typical iteration, the boundary point switching operation is carried out on all of the switching components to which the greatest probability has been given. At that probability, the solution is reached (per iteration). During the subsequent iteration, the boundary points, envelop points, and boundary point switching components in the newly acquired solution will once again be recognized, and a new probability assignment will be performed in accordance with the category of boundary points and envelop points.

3.4.3 The Finishing Touches

We have arrived at the optimal answer after the iterations have been completed. The stopping criteria have been determined to be when either the change in the assignment of probabilities to the switching components is not significant (not possible), or when the change in the assignment of probabilities does provide the possibility of a change in the measurement of convexity (or in the value of the cost/fitness function), whichever is achieved earlier.

3.5 DESCRIPTION AND APPLICATION OF THE RECONSTRUCTION ALGORITHM

The reconstruction method that has been presented is implemented as

Step 1: Get the starting solution 0 by using algorithm 2.7.2, and then put tm:= Maxt and niter:=1

The second step is to locate the collection of points that constitute F's envelope as well as its border, denoted by BF and EF respectively.

Step 3: Exit the program if niter is more than tm.

Step 4: Locate all boundary point switching components for each individual element of the BF, and then, based on the category of these components, give the probability with the greatest value to the switching component that has an isolated point or a type 4 boundary point. And apply the probability to each switching component based on the kind of boundary point working your way down the list.

5. Carry out the switching operation on the switching components while maintaining the highest probability in

Step 6: set niter = niter + 1. If there is an increase in the value of the cost function Nhv, then Proceed to step 2 and set tm such that it equals niter plus max. Else Proceed to step 4, then choose another component in BF that has the next greatest likelihood to carry out the switching operation and raise it.

Step 7: If there is not a considerable improvement at this point, repeat steps 2 through 6.

4. RESULT FROM ANALYSIS

FOR THE PURPOSE OF CONDUCTING AN EXPERIMENT, A TEST SET OF CONVEX BINARY IMAGES WITH THE FOLLOWING DIMENSIONS 10 BY 10, 20 BY 20, 30 BY 30, 40 BY 40, 50 BY 50, 60 BY 60, 70 BY 70, 80 BY 80, 90 BY 90, AND 100 BY 100 ARE GENERATED; FOR EACH OF THESE DIMENSIONS, A SET OF ONE HUNDRED IMAGES HAS BEEN PRODUCED. THE HORIZONTAL AND VERTICAL PROJECTIONS OF EACH PICTURE ARE COMPUTED BY ADDING THE ROWS AND COLUMNS OF THE ASSOCIATED BINARY MATRICES. THIS IS DONE FOR EACH IMAGE. THEREFORE, A PICTURE THAT IS NXN PIXELS IN SIZE WILL HAVE ITS PROJECTION SET TO (R, C) WITH AND. FIGURE 5.1 ILLUSTRATES A COMMON EXAMPLE OF A BINARY PICTURE WITH DIMENSIONS OF 20 BY 20, ALONG WITH ITS ASSOCIATED PROJECTION SET (R, C).

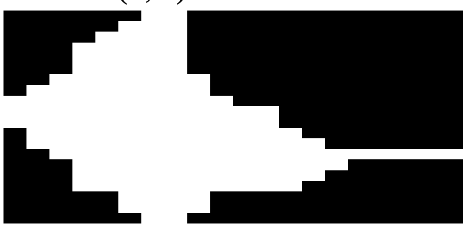

Figure 5.1: Image 20x20 and its Projection Set

$R = \{2, 3, 4, 5, 5, 5, 7, 8, 10, 12, 12, 12, 13, 18, 12, 11, 10, 4, 4, 2\}$

$C = \{3, 6, 8, 14, 15, 18, 20, 20, 13, 9, 8, 8, 6, 4, 2, 1, 1, 1, 1, 1\}$

On these image sets we implemented the proposed reconstruction algorithm 5.6.1; we also implemented the algorithm given in on these images.

The average value of n_{hv} and average reconstruction error (E_R) for different sizes of images ranging from 10x10 to 100x100 are reported. The average is taken on a complete set of 100 images in each size. The convergence of both algorithms concerning the convexity measure is reported for a typical image of size 40 x 40. It is experiential that the algorithm converges faster than the algorithm. Further to test the stability of the algorithm we added discrete uniform random noise in calculated projections and the reconstruction by these algorithms is obtained using these noisy projections. For adding noise in projection data, we generated discrete uniform random number from {-k, -k+1, …, -1, 0, 1, …, k-1, k} for k=1, 2, 3, 4 and 5. These are referred here as 1%, 2%, 3%, 4% and 5% noise in projection data.

The convergence of our algorithm 5.6.1 and the algorithm [jerry] with noisy projection data concerning convexity measure for a typical image of size 40x40 are reported in table 5.5 to table 5.9 and their graphical representations are given in figure 5.9 to 5.13. Further, the average and average in the reconstruction of each size of image with noisy projections are reported. The convexity of the algorithm has been image after the application of the reconstruction solution.

5. CONCLUSION

The process of producing a picture as a result of projection data is referred to as image reconstruction. There are a great number of different kinds of projection data, all of which may be acquired from the input picture matrix. The primary image projection data is collected from the input picture matrix in the form of horizontal, vertical, horizontal-vertical, diagonal, and anti-diagonal projections. The numerous apps that are used in this method of image matrix reconstruction were utilized to get the binary image matrix. The image matrix reconstruction approach that was employed for the suggested model is based on both Chang's algorithm and the genetic algorithm. Both of these algorithms were developed by Chang. In order to complete the last step of recovery, the genetic algorithm is applied to the post matrix. When we speak about genetic algorithms, we are referring to an optimization algorithm that is founded on the foundations of the genetic reproduction process. It is generated via the fundamental components or functions that are developed by mixing crossing mutations with the generation of new populations. This is the function that it is formed through. There are many different computer applications that need optimization, and genetic algorithms are employed in many of those applications. The suggested model is validated using a wide range of binary pictures, with image sizes ranging from 10*10 to 100*100. In the section titled "Results Evaluation," the outcomes of any and all experiments that took place during the course of this research are presented in tabular format. Additionally, this section outlines the outcomes of the many rounds of experiments that took place regarding the reconstruction of the image. Experimental findings about the emergence of temporal complexity and reconstruction error have been gleaned from this work. When compared to the model that was suggested, the reconstruction error that was recorded in the current body was much smaller. Recorded with a difference of around 80%. This is a significant advance in the post-model.

6. FUTURE SCOPE

There is a chance that in the not-too-distant future, the temporal complexity of the model that has been presented might be reduced. The paradigm of the genetic algorithm makes it possible to develop it extremely rapidly. Additionally, a model that is superior to the genetic algorithm is able to be constructed.

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