An Application of Combinatorial Analysis HGLC for Image restoration

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Abstract: Graphs are very powerful tools for describing many problems and structures in image processing. But graphs only describe some binary relations and are not always sufficient for modeling some complex problems or data. In order to overcome these difficulties and to provide a more viable tool for processing images by taking into account the topological and geometrical aspects of an image, combinatorial or hypergraph model is proposed. A relatively new class of algorithm termed combinatorial algorithm relies on approach to image processing. Combinatorics refers to arranging the elements into sub sets. This project aims three applications in particular to Denoising of Image, Image compression and Image Edge detection using combinatorial analysis. First the image can be converted into Hypergraph model by using Image Adaptive Neighborhood Hypergraph (IANH) model then this model can be used for different applications of image processing. Impulse noise is detected by analysing unit cardinality pixels in IANH model, that can be removed by different traditional methods and comparing PSNR and BER of these methods. In this project relates to a new method for lossless image compression, based on combinatorial (Hypergraph) analysis HGLC (Hyper Graph Lossless Compression). First the image can be represented into Hypergraph model by using IANH model. Then it can be modeled into number of rectangles to remove redundant data using algorithm to compress the image.
Keywords: Image compression, lossy, Lossless ,Image restoration,Hypergraph.

1. INTRODUCTION

In many areas of research such as Image processing, Criminology, Artificial intelligence, etc., the relation between objects expressed by binary relations. The area which models these relations is combination of graph theory and image processing. In a graph the vertices models to objects and edges corresponds to the interrelations of these objects. A digital image can also be considered as a graph when the topography (connectivity) of the support grid is taken into detail. But it is difficult to model the direct graph into image, so we go for hyper graphs which expressed by binary relations.

Combinatorial (Hypergraph) theory initially proposed by Berge [5] it is generalization of graph theory by grouping sets into edges, then combining these edges into family of Hypergraph. This mathematical concept can be represented to networks, communication systems, process scheduling, data structures and a variety of other systems where connectivity between the objects in the system play a dominant role. We can consider it as a model of image applications.

Image compression gives the problem of reducing amount of data needed to represent a digital image. This eliminates redundant data in image. This may be lossy or lossless. In this paper proposed a new method for lossless image compression, based on combinatorial (Hypergraph) analysis and called HGLC (Hyper Graph Lossless Compression). First the image can be represented into Hypergraph model by using IANH model. Then it can be modelled into number of rectangles to remove redundant data using algorithm to compress the image.

Edge detection is one of the fundamental steps in computer vision. Generally, the first stage of edge detection is the interpretation of derivatives of the image intensity. Smoothing filters are used as regularization techniques to make differentiation more immune to noise. This project leads to develop an edge detection algorithm based on a geometric property of the IANH model. This is two stage approach first stage is representation of image into IANH model. The second stage is classification of hyper edges into region based on the combinatorial definitions.

1.1 Introduction To Combinatorial Analysis

An image is essentially a 2-D signal processed by the human visual system. The signals representing images are usually in analog form. However, for processing, storage and transmission by computer applications, they are converted from analog to digital form. A digital image is basically a 2- Dimensional array of pixels. Each pixel has intensity value and location address.

Graphs are very powerful tools for describing many problems and structures in image processing. But graphs only describe some binary relations and are not always sufficient for modelling some complex problems or data. In order to overcome these difficulties and in order to provide a more viable tool for processing images by taking into account the topological and geometrical aspects of an image, hypergraph model is proposed.

1.2 Related Work:

In this work the digital image can be represented into Hypergraph using the IANH Model for different applications. The digital image is a two dimensional discrete form this is digitized in both spatial and magnitude feature value. The digital image can be represented by

$$I : X \subseteq Z^2 \rightarrow C \subseteq Z^n \text{ with } n \geq 1 \qquad (1.1)$$

Where C denotes the *feature intensity level* and X denotes a set of image points. The set (x, I(x)) is called a pixel which is acronym for picture element. Assume d be a distance on C, then the neighbourhood relation on an image is given by

$$\forall x \in X, \Gamma_{\alpha,\beta}(x) = \{x' \in X, x' \neq x \mid d(I(x), I(x')) < \alpha \text{ and } d'(x, x') \leq \beta\} \qquad (1.2)$$

Where $\Gamma_\beta(x)$ is neighbourhood of x on the grid of β If β=4 it is the 4 neighbourhood. If β=8 then it is 8 neighbourhood. The image can be represented as hyper graph called Image Adaptive Neighbourhood Hypergraph(IANH) which is denoted by $H_{\alpha,\beta}$ which is defined by

$$H_{\alpha,\beta} = (X, (\{x\} \cup \Gamma_{\alpha,\beta}(x))_{x \in X}) \tag{1.3}$$

The attribute α is standard deviation of centre pixel and its neighbourhood pixels i.e.,

$$\{x\} \cup \Gamma_\beta(x).$$

2. IMAGE COMPRESSION

The purpose of compression is to code the image data into a compact form, minimizing both the number of bits in the representation, and the distortion caused by the compression .the importance of image compression is emphasized by the huge amount of data in raster images, a typical gray-scale image of 512 x 512 pixels, each represented by 8bits, contains 256 kilobytes of data. With the color information, the number of bytes is tripled. The video images of 25 frames per second, even a one second color film requires approximately 19 Megabytes of Memory. To handle and process the above said data representation definitely one has to think of how to represent in terms of the encoded data the method is called compression, obliviously this technique becomes mandatory for any kind of present day digital image data processing.

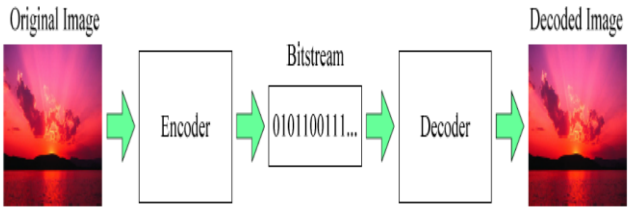


Fig 1.Basic flow of image compression coding.

Image compression coding is to store the image into bit-stream as compact as possible and to display the decoded image in the monitor as exact as possible. Now consider an encoder and a decoder as shown in Fig.1. When the encoder receives the original image file, the image file will be converted into a series of binary data, which is called the bit-stream. The decoder then receives the encoded bit-stream and decodes it to form the decoded image. If the total data quantity of the bit-stream is less than the total data quantity of the original image, then this is called image compression.

The compression ratio is defined as follows:

$$CR = n1 / n2 \tag{2.1}$$

where n_1 is the data rate of original image and n_2 is that of the encoded bit-stream.

As shown in the figure 1, the encoder is responsible for reducing the coding, interpixel and psychovisual redundancies of input image. In first stage, the mapper transforms the input image into a format designed to reduce interpixel redundancies.

The second stage, quantizer block reduces the accuracy of mapper's output in accordance with a predefined criterion. In third and final stage, a symbol decoder creates a code for quantizer output and maps the output in accordance with the code. These blocks perform, in reverse order, the inverse operations of the encoder's symbol coder and mapper block. As quantization is irreversible, an inverse quantization is not included in the figure 1.

Two common used measurements are the **Mean Square Error (MSE)** and the **Peak Signal to Noise Ratio (PSNR)**, which estimate the difference between the original image and the decoded image *f(x,y)* is the pixel value of the original image, *f'(x,y)* is the pixel value of the decoded image.

$$MSE = \sqrt{\frac{\sum_{x=0}^{m-1}\sum_{y=0}^{n-1}[f(x,y) - f'(x,y)]^2}{mn}} \tag{2.2}$$

$$PSNR = 20\log_{10}\left(\frac{255}{MSE}\right) \tag{2.3}$$

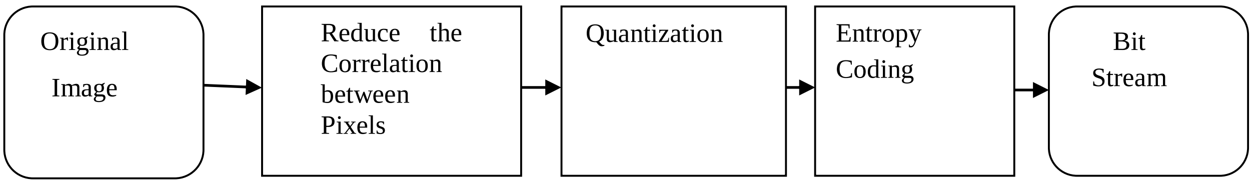


Fig. 2. General encoding flow of Image compression

The general encoding architecture of image compression system is shown is Fig. 2.Once the correlation between the pixels is reduced, the advantage of statistical characteristics and the variable length coding theory to reduce the storage quantity. The best-known methods are Predictive Coding, Orthogonal Transform, Subband Coding.

The objective of quantization is to reduce the precision and to achieve higher compression ratio. The shortcoming of quantization is that it is a lossy operation, which will result into loss of precision and unrecoverable distortion. The image compression standards such as JPEG and

JPEG 2000 have their own quantization methods.Entropy coding is to achieve less average length of the image. Entropy coding assigns code words to the corresponding symbols according to the probability of the symbols.

2.1 IMAGE COMPRESSION TECHNIQUES

The image compression techniques are broadly classified into two categories, they are: Lossless techniques and Lossy techniques. In our research work we consider one lossy compression (K-RLE) and one lossless compression algorithms (RLE) on a standard Leena image data file (512x512x8).we evaluate the performance of these algorithms by calculating or measuring the typical parameters discussed in the above section.

2.1.1 LOSSLESS COMPRESSION TECHNIQUE

In lossless compression techniques, the original image/data can be perfectly recovered from the compressed (encoded) image/data. These are also called noiseless since they do not add noise to the signal (image).It is also known as entropy coding since it use statistics or decomposition techniques to eliminate or minimize redundancy. Lossless compression is used only for a few applications with stringent requirements such as medical imaging and sensor data processing, ***In our research work we consider the basic lossless compression technique named as Run Length Encoding (RLE),*** earlier researchers implemented the RLE compression algorithm on low cost, low power tinny embedded systems (based on 8bit/16bit microcontrollers) using ALP and respective EC programming for slowly varying sensor data for wired and wireless sensor networks (WSN). Even they evaluated the performance of RLE on Reconfigurable FPGA Architecture for above said applications [5]. Probably no one analyzed design exploration of image data compression using RLE. In our research work we analyze and evaluate the performance of RLE compression algorithm for image data applications based on MATLAB EDA Tools

Run – Length Encoding:

- The Idea behind this algorithm is, If a data item d occurs n consecutive times in the input data we replace the n occurrences with the single pair nd.
- Run-Length Encoding (RLE) is a basic compression algorithm. It is very useful in case of repetitive and slowly varying data items.
- This is most useful basic compression algorithm on data that contains many such runs: for example, relatively simple graphic images such as icons, line drawings, and grayscale images.
- Which is a lossless data compression algorithm used for slowly varying sensor and image data.
- It is not useful with files that don't have many runs as it could double the file size.

82	82	82	82	82	89	89	89	89	90	90

{82,5}	{89,4}	{90,2}

Figure.3: Run Length Encoding

2.1.2 LOSSY COMPRESSION TECHNIQUE

Lossy schemes provide much higher compression ratios than lossless schemes. Lossy schemes are widely used since the quality of the reconstructed images is adequate for most applications .By this scheme, the decompressed image is not identical to the original image, but reasonably close to it.

Run Length Encoding with K - Precision:

The idea behind this new proposed algorithm is this: let K be a number, a data item d or data between d+K and d-K occur n consecutive times in the input stream, replace the n occurrences with the single pair nd. We introduce a parameter K which is a precision.

- If K = 0, K-RLE is RLE. K has the same unit as the dataset values, in this case degree.

13	14	15	14	8
9	10	10	10	11
	10	10	10	8
91	8	13	14	15

Figure.4: A non trivial image matrix

- K-RLE is a lossy compression algorithm.
- This algorithm is lossless at the user level because it chooses K considering that there is no difference between the data item d, d+K or d-K according to the application.

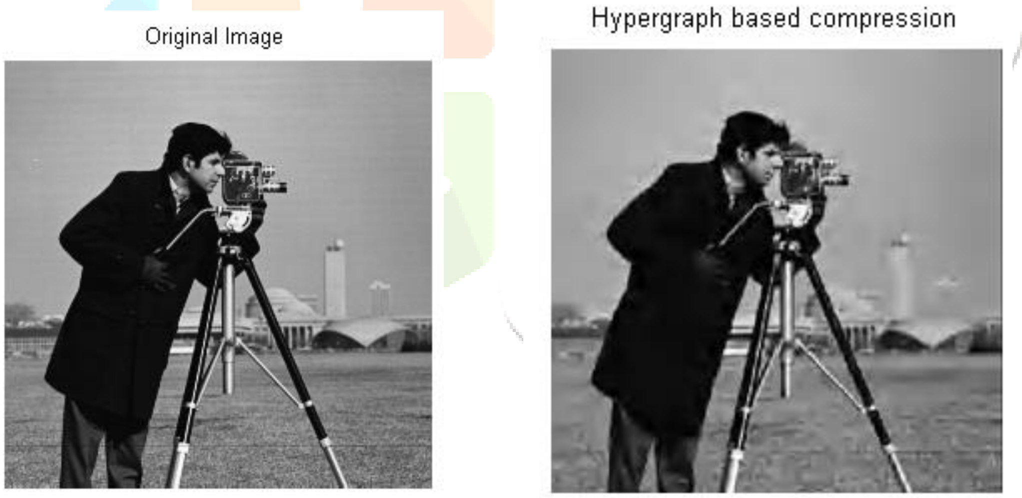
2.2 Image Compression using Combinatorial Analysis

A rectangle can be stored as a couple of points. But such representation required several bytes. Let's consider the case of a one-pixel black/white checkerboard pattern. The hypergraph associated to this image will contains as many rectangles as there are pixels in the image and each rectangle will require more than one byte for storing it. So the rectangles hypergraph will be bigger than the original uncompressed image. For that reason, introduce an integer K and use the following process for compressing and image I:

- Build H(I), is the hypergraph representation of I.
- Order the hyperedges of H(I) following surface (the bigger rectangle comes first). If two rectangles have the same surface the first one is the first constructed. The ordered hyperedges are called $\{R_1, \ldots, R_m\}$. The ordered hypergraph is called $H_0(I)$.

- Extract from $H_0(I)$ a partial hypergraph $H_k(I)=\{R_x \in \{R_1,\ldots,R_m\}; x \in X\}$. The set of indices X is chosen such that for all x Є X, R_x contains at least K pixels that are not in $\bigcup_{i \in X, i<x} R_i$ (X can be empty). The partial hypergraph $H_K(I)$ depends on K. One can note that if K = 0 then $H_K(I) = H_0(I)$.
- Store the hyperedges of $H_K(I)$. With a good representation between 3 and 9 bytes are required for a rectangle, plus the color.
- Create an empty data segment.
- Create an empty surface S of the size of the image with one flag per pixel. Set all the flags to 0.
- Read the hypergraph $H_K(I)$ and draw all the rectangles on S. For each pixel drawn, set the corresponding flag to 1.
- Traverse the image and, for each flag set to 0, write the pixel color in the data segment. The colors are written linearly so no additional data are required.
- Compress the hypergraph and the data segment with a PPM-based algorithm.
  The images used for compression are lena and cameraman images shown in Fig.5 & 6 respectively. The output when it is subjected to hypergraph or combinatorial compression is shown in Figures respectively.

Fig.5. Hypergraph based image compression



(a) (b)

Fig.6. Results of Hypergraph based compression for Cameraman image
(a) Original image, (b) Hypergraph based compression

The output image having PSNR and MAE values are 60.43 and 0.52 respectively for lena image, 54.52 and 0.46 respectively for cameraman image.

3. Edge Detection

In edge detection, one approach is to track pixels column wise (or, row wise) before using statistical measures for the processing. Graph-based approach [4] identifies binary-related pixels before processing them. Graphs are mathematical modelling tools for low-level image processing applications because graphs are essentially about relationships between objects (these are pixels in images). But graphs do not go beyond binary relations, and pixel relations in images are, in most applications, complex and not necessarily binary. Hence a model that can accommodate higher order relations would be desirable and valuable. Hypergraphs do precisely that they accommodate higher order object relations.

3.1 Edge Detection Operators

There are numerous edge operators available. Present gradient operators as a measure of edge sheerness can be divided into three categories:

1. Operators approximating the derivatives of the image function using finite differences (e.g. Roberts, Prewitt, Sobel, Laplace, Robinson, Kirsh, Compass edge operators),
2. Operators based on the zero crossings of the second derivatives of the image function (e.g. Marr-Hildreth or Zero Crossing, Laplacian of Gaussian, Canny edge detector) and
3. Operators which attempt to match an image function to a parametric model of edges (parametric operators).

3.2 Canny's Edge Detection Algorithm:

The Canny edge detection algorithm is known to many as the optimal edge detector. Canny's intentions were to enhance the many edge detectors already out at the time he started his work. He was very successful in achieving his goal and his ideas and methods can be found in his paper, "*A Computational Approach to Edge Detection*". In his paper, he followed a list of criteria to improve current methods of edge detection.

Based on these criteria, the canny edge detector first smoothes the image to eliminate and noise. It then finds the image gradient to highlight regions with high spatial derivatives. The algorithm then tracks along these regions and suppresses any pixel that is not at the maximum (nonmaximum suppression). The gradient array is now further reduced by hysteresis. Hysteresis is used to track along the remaining pixels that have not been suppressed. Hysteresis uses two thresholds and if the magnitude is below the first threshold, it is set to zero (made a nonedge). If the magnitude is above the high threshold, it is made an edge. And if the magnitude is between the 2 thresholds, then it is set to zero unless there is a path from this pixel to a pixel with a gradient above threshold

3.3 Combinatorial Edge Detection

Important aspect of image analysis is edge detection. In a gray level image containing homogeneous objects, an edge is a boundary between two regions of different constant gray levels. If the difference is clear-cut between regions have ideal edges. Ideal edges, however, are not what one finds in the images produced by image devices, and other imaging devices. There are several factors that degrade edges, such as noise, irregularities of the surfaces structure of objects, etc. So a number of methods have been devised to solve the edge detection problem. Here an edge detection algorithm developed based on a geometric property of the IANH model. This algorithm finds the intersecting family with an empty intersection. The pixels belonging to these families are labeled as edges.

A digital gray image labelled I (and assumed noise-free) is mathematically represented by the function I: $V \rightarrow W$ (where $V \subseteq N \times N$ and W is the set of non-negative integers), where for $a = (x, y) \in V$, I (a) is the gray scale intensity value of the pixel a located at (x, y) $\in N \times N$, so that it is natural to think of the image I as a nonempty finite subset V of N x N. Let V be endowed with the chessboard metric ρ.

Let L be a positive integer, $L \leq 254$ and $q = [255 - 255(\text{mod } L)] / L$. Set the parameters of hyper edges E_1 to E_{q+1} as

(a) $E_1 = \{a \in V \mid 0 \leq I(a) \leq L\}$,

(b) $E_k = \{a \in V \mid (k-1) L + 1 \leq I(a) \leq k L\}$ for k = 2, …, q,

(c) $E_{q+1} = \{a \in V \mid q L + 1 \leq I(a) \leq 255\}$. Obviously the Et (t = 1..., q +1) are subsets of V, some possibly empty (φ).

Let $E = Et \mid t = 1$ through q + 1; and $Et \neq \varphi\}$. Then E is a set of nonempty subsets of V, and E fills out V. The graph set H = (V, E), then H is a hypergraph on the set V, and thereby is a hypergraph representation of the image I.

The algorithm for edge detection is shown in Fig. 4.4, in that first the gray image is converted into hypergraph by IANH model, then identify the interior points in hyper edge, by suppressing the interior points results in edges of the image.

The results of each of the three algorithms (Sobel, Canny and Combinatorial) on these two images are given in panels Fig.4.7 and Fig. 4.8 respectively.

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

Fig.7. Comparison of (a) original (b) Sobel and (c) Canny algorithms with (d) Proposed algorithm for Cameraman image

CONLCUSION:

Combinatorics do precisely accommodate higher order object relations in images, these have many applications and research works have shown that combinatorics to be excellent tools in image processing. Hypergraph theory can be an effective approach to low level image processing.

Three applications in particular to Denoising of Image, Image compression and Image Edge detection based on combinatorial analysis are proposed. Hypergraph based CHM filter effectual in removing Salt and Pepper noise, but it has a drawback: it tends to blur the image. On the other hand, in HG image representation, the parameters α and β track the image by means of hyperedges, which results in a better distinction of SP noise. HGRMS also limitation that it leaves few stars unprocessed. The ability of the proposed HTMR filter to deal with these artifacts while restoring the fine details of images. Hypergraph based image compression IANH model can be modeled into number of rectangles to remove redundant data using algorithm to compress the image. Edge detection is a very important step for extracting features of an image which may be used for image identification. The edge detection algorithm in noisy images is implemented and tested for synthetic and real images. A new algorithm of edge detection based on properties of hypergraph theory has been proposed. It proves to give results that are as good as an even better than Sobel's edge detection method based on gradient and Canny method. The results of the tests described show our algorithm to be accurate, robust on both synthetic and real image corrupted by noise.

FUTURE WORK:

In fact hyper graphs are very promising tools and can be applied in many other images process. Further works will be focused on:

- Conception of algorithms in high level image processing using hypergraphs (by example for shape recognition).
- Hypergraph-based compression for 3D images.
- Hypergraph-based entropy on 2D and 3D images.
- Generalizations of the IANH for 3D images, generalization inducing some segmentation, edge detection and noise cancellation algorithms on 3D images.

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