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Improvement in Image Compression ratio using proposed Algorithm

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ABSTRACT

This paper presents a neural network based technique that may be applied to image compression. Conventional techniques such as Huffman coding and the Shannon Fano method, LZ Method, Run Length Method, LZ-77 are more recent methods for the compression of data. We use a multi-dimensional, multi-resolution histogram pyramid to partition the feature space into increasingly larger regions. At the finest resolution level in the pyramid, the partitions (bins) are very small; at successive levels they continue to grow in size until a single bin encompasses the entire feature space. At some level along this gradation in bin sizes, any two particular points from two given point sets will begin to share a bin in the pyramid, and when they do, they are considered matched. The key is that the pyramid allows us to extract a matching score without computing distances between any of the points in the input sets—the size of the bin that two points share indicates the farthest distance they could be from one another. We show that a weighted intersection of two pyramids defines an implicit partial correspondence based on the smallest histogram cell where a matched pair of points first appears.

Keywords:—*Neural Network, Image Compression, Kohonen network.*

I. INTRODUCTION

Every image is identified using its unique set of features. The se features are exclusive for each image and hence help in subsequent identification and discrimination between images. Features can be characterized as the interest focuses or an "interesting" part of a picture, which are utilized as a beginning stage for some computer vision calculations [9][10]. Since, components are utilized as the beginning stage and principle primitives for resulting algorithms, the general algorithm will regularly just be in the same class as its feature detector. Therefore, the alluring property for a feature detector is repeat ability: regardless of whether the same feature will be identified in two or more diverse pictures of the same scene. Feature identification is a low-level image processing operation. That is, it is typically executed as the main operation on a picture, and analyzes each pixel to check whether there is a component present at that pixel. On the off chance that this is a part of a bigger algorithm, then the calculation will regularly just inspect the picture in the locale of the features [4][6][9].

In computer vision and image processing the idea of feature identification alludes to techniques that go for figuring deliberations of picture data and settling on nearby choices at each image point whether there is an image feature of a given sort by then or no [14]

Earlier work in content-based image retrieval focused on global representations that describe each image with a single vector of attributes, such as a color histogram, or an ordered list of intensity values or filter responses. While vector rep- presentations permit the direct application of standard distance functions and indexing structures, they are known to be prohibitively sensitive to realistic image conditions. For example, consider stacking the images in Figure 2 one on top of the other, and then checking the intensity at any given pixel for each example—it is quite likely that few of them would be in agreement, even though each image contains a koala as its most prominent object. Coding redundancy is present when less than optimal code words are used. Inter pixel redundancy results from correlations between the pixels of an image. Psycho visual redundancy is due to data that is ignored by the human visual system (i.e. visually non essential information). Image compression techniques reduce the number of bits required to represent an image by taking advantage of these redundancies. [14]

2. Related Work for Data Compression

2.1 Huffman Coding

Huffman coding is a widely used compression method. With this code, the most commonly used characters contain the fewest bits and the less commonly used characters contain the most bits. It creates variable-length codes that contain an integral number of bits. Huffman codes have the unique prefix attribute, which means they can be correctly Fano method, Statistical modeling and their variations. Decoded despite being of variable length.[15] A binary tree is used to store the codes. It is built from the bottom up, starting with the leaves of the tree and working progressively closer to the root. The procedure for building the tree is quite simple. The individual symbols are laid out as a string of leaf nodes that are going to be connected to the binary tree. Each node has a Weight, which is simply the probability of the symbol's appearance. The main disadvantage of Huffman Coding are

1. The Compression ratio is low at higher size of image file
2. The efficiency is lowest
3. The redundancy is not reduced

In Huffman coding, the binary strings or codes in the encoded data are all different lengths. This makes it difficult for decoding software to determine when it has reached the last bit of data and if the encoded data is corrupted. in other words it contains spurious bits or has bits missing it will be decoded incorrectly and the output will be nonsense.

2.2. Shannon-Fano Method

Shannon–Fano coding is a technique for constructing a prefix cod based on a set of symbols and their probabilities (estimated or measured). It is suboptima in the sense that it does not achieve the lowest possible expected code word length like Huffman codin; however unlike Huffman coding, it does guarantee that all code word lengths are within one bit of their theoretical ideal[15].

In Shannon–Fano coding, the symbols are arranged in order from most probable to least probable, and then divided into two sets whose total probabilities are as close as possible to being equal

The main disadvantage of Shannon-Fano Coding is following

1. In Shannon-Fano coding, we cannot be sure about the codes generated. There may be two different codes for the same symbol depending on the way we build our tree.

2. Also, here we have no unique code i.e a code might be a prefix for another code. So in case of errors or loss during data transmission, we have to start from the beginning.

3. Shannon-Fano coding does not guarantee optimal codes.

Hence, Shannon-Fano coding is not very efficient

2.3. Arithmetic Coding

Arithmetic coding [4] bypasses the idea of replacing input symbols with a single floating point output number. More bits are needed in the output number for longer, complex messages. This concept has been known for some time, but only recently were practical methods found to implement arithmetic coding on computers with fixed sized-registers. The output from an arithmetic coding process is a single number less than 1 and greater than or equal to 0. The single number can be uniquely decoded to create the exact stream of symbols that went into construction. Arithmetic coding seems more complicated than Huffman coding, but the size of the program required to implement it, is not significantly different. Runtime performance is significantly slower than Huffman coding. If performance and squeezing the last bit out of the coder is important, arithmetic coding will always provide as good or better performance than Huffman coding. But careful optimization is needed to get performance up to acceptable levels.

There are a few disadvantages of arithmetic coding. One is that the whole codeword must be received to start decoding the symbols, and if there is a corrupt bit in the codeword, the entire message could become corrupt. Another is that there is a limit to the precision of the number which can be encoded, thus limiting the number of symbols to encode within a codeword

2.4 LZ-77

Another technique for data compression is LZ-77 encoding [7]. This technique is a simple, clever, and effective approach to compress text. This technique exploits the fact that words and phrases within a text stream are likely to be repeated. When they repeat, they can be coded as a pointer to an earlier occurrence, with the pointer accompanied by the number of characters to be matched. This technique is useful for compressing text because it able to reduce the file size and increase the compression ratio after compression. However, it is not efficient for image file format such bmp, gif, tif and tiff. Beside that, this technique will take several minutes to compress a data. Sometimes, the long processing time will cause the missing of some characters.

The main disadvantage of LZ-77 is

1. This algorithm is time consuming

2. LZ77 is the limited size. When the data size is high for compression then mostly data reduced or corrupt during compression

2.5 LZW Method

The most popular technique for data compression is Lempel Ziv Welch (LZW) [8]. LZW is a general compression algorithm capable of working on almost any type of data. It is generally fast in both compressing and decompressing data and does not require the use of floating-point operations. LZW technique also has been applied for text file. This technique is very efficient to compress image file such tiff and gif. However, this technique not efficient for compress text file because it require many bits and data dictionary.

The main disadvantage of LZW-77 is

1. This technique is most expensive other compression technique
2. Mostly content are lost during compression step

2.6 Run Length Method

One of the techniques for data compression is "run length encoding", which is sometimes knows as "run length limiting" (RLL) [5, 6]. Run length encoding is very useful for solid black picture bits. This technique can be used to compress text especially for text file and to find the repeating string of characters. This compression software will scan through the file to find the repeating string of characters, and store them using escape character (ASCII 27) followed by the character and a binary count of he number of items it is repeated.

The main disadvantage of Run length algorithm is

1. First problem with this technique is the output file is bigger if the decompressed input file includes lot of escape characters.
2. Second problem is that a single byte cannot specify run length greater than 256.
3. they disconnect the outer error-correcting code from the bit-by-bit likelihoods that come out of the channel

So, we apply the proposed approach such as GSOM Algorithm that can remove the above disadvantage of various traditional algorithms GSOM Provide optimal value of compression ratio of image file. It require no more time for compression.

3. Neural Network Based Method for Image Compression

Artificial Neural Networks have been applied to many problems [3][11], and have demonstrated their superiority over classical methods when dealing with noisy or incomplete data. One such application is for data compression. Neural networks seem to be well suited to this particular function, as they have an ability to preprocess input patterns to produce simpler patterns with fewer components[16],[9]. This compressed information (stored in a hidden layer) preserves the full information obtained from the external environment. The compressed features may then exit the network into the external environment in their original uncompressed form. The main algorithms that shall be discussed in ensuing sections are the Back propagation algorithm and the Kohonen self-organizing maps.

3.1 Back propagation Neural Network

The Back propagation (BP) algorithm [12] has been one of the most successful neural network algorithms applied to the problem of data compression [10]. The data compression problem in the case of the BP algorithm is posed as an encoder problem. The data or image to be compressed passes through the input layer of the network, and then subsequently through a very small number of hidden neurons. It is in the hidden layer that the compressed features of the image are stored, therefore the smaller the number of hidden neurons, the higher the compression ratio. The output layer subsequently outputs the decompressed image to the external environment. It is expected that the input and output data are the same or very close. If the image to be compressed is very large, this may sometimes cause difficulty in training, as the input to the network becomes very large. Therefore in the case of large images, they may be broken down into smaller, sub-images [9]. Each sub-image may then be used to train an individual ANN.

The main disadvantage of Back propagation algorithm is

1. In this technique, the error rate is high during image compression
2. It take more time for image compression and decompression
3. It is expensive technique
4. This technique is apply only for specific image format such as BMP, JPG, GIF

So, we apply the proposed approach such as GSOM Algorithm that will remove the above disadvantage and improve the compression ratio with quality and provide better result compared to traditional compression algorithm.

4. Proposed Techniques for Image Compression

4.1 Growing Self Organizing Map Algorithm

A growing self-organizing map (GSOM) is a growing variant of the popular self-organizing ma (SOM). The GSOM was developed to address the issue of identifying a suitable map size in the SO. It starts with a minimal number of nodes (usually 4) and grows new nodes on the boundary based on a heuristic. By using the value called Spread Factor (SF), the data analyst has the ability to control the growth of the GSOM.

All the starting nodes of the GSOM are boundary nodes, i.e. each node has the freedom to grow in its own direction at the beginning. New Nodes are grown from the boundary nodes. Once a node is selected for growing all its free neighboring positions will be grown new nodes. In GSOM, input vectors are organized into categories depending on their similarity to each other. For data compression, the image or data is broken down into smaller vectors for use as input. For each input vector presented, the Euclidean distance to all the output nodes are computed. The weights of the node with the minimum distance, along with its neighboring nodes are adjusted. This ensures that the output of these nodes is slightly enhanced. This process is repeated until some criterion for termination is reached. After a sufficient number of input vectors have been presented, each output node becomes sensitive to a group of similar input vectors, and can therefore be used to represent characteristics of the input data. This means that for a very large number of input vectors passed into the network, (uncompressed image or data), the compressed form will be the data exiting from the output nodes of the network (considerably smaller number). This compressed data may then be further decompressed by another network. We take 50 neuron as a one input hidden layer and one output layer we take learning rate 0.5. the compression and decompression figure of GSOM Algorithm are following

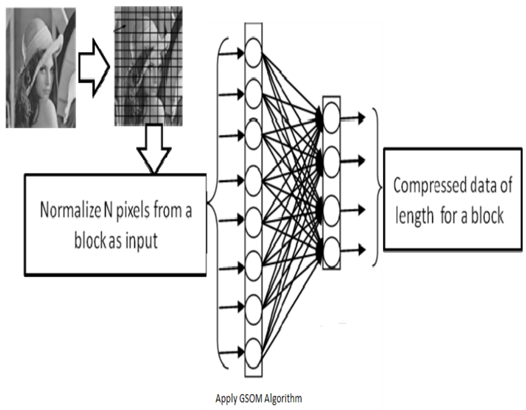

Figure 1: GSOM Architecture compression

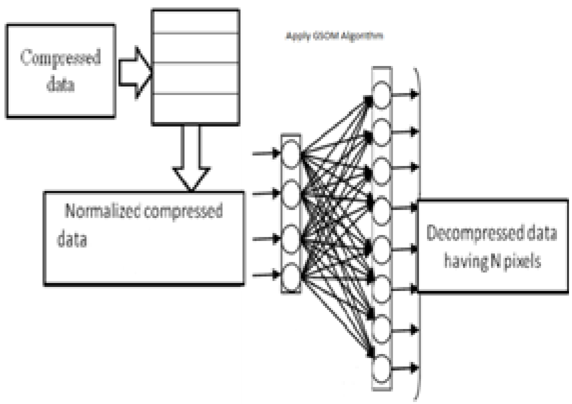

Figure 2: GSOM Architecture Decompression

4.2 The Learning Algorithm of the GSOM:

The GSOM process is as follows:

A. Initialization phase:

Initialize the weight vectors of the starting nodes (usually four) with random numbers between 0 and 1.

Calculate the growth threshold) GT for the given data set of dimension D according to the spread factor) SF using the formula

$$GT = -D \times \ln(SF)$$

B. Growing Phase:

1. Present input to the network.

2. Determine the weight vector that is closest to the input vector mapped to the current feature map (winner), using Euclidean distance. This step can be summarized as: find q' such that $|v - w_{q'}| \leq |v - w_q| \forall q \in \mathbb{N}$ where, v a w re the input and weight vectors respectively, q is the position vector for nodes and $\mathbb{N}$ is the set of natural numbers.

3. The weight vector adaptation is applied only to the neighborhood of the winner and the winner itself. The neighborhood is a set of neurons around the winner, but in the GSOM the starting neighborhood selected for weight adaptation is smaller compared to the SOM (localized weight adaptation). The amount of adaptation (learning rate) is also reduced exponentially over the iterations. Even within the neighborhood, weights that are closer to the winner are adapted more than those further away. The weight adaptation can be described by

$$w_j(k+1) = \begin{cases} w_j(k) & \text{if} j \notin \mathrm{N}_{k+1} \\ w_j(k) + LR(k) \times (x_k - w_j(k)) & \text{if} j \in \mathrm{N}_{k+1} \end{cases}$$

where the Learning Rate, $LR(k)$ $k \in \mathbb{N}$ is a sequence of positive parameters converging to zero as. $k \to \infty$, $w_j(k)$ $w_j(k+1)$ are the weight vectors of the node j before and after the adaptation and N_{k+1} is the neighborhood of the winning neuron at the $(k+1)$ th iteration. The decreasing value of $LR(k)$ in the GSOM depends on the number of nodes existing in the map at time. k

4. Increase the error value of the winner (error value is the difference between the input vector and the weight vectors).

5. When($TE_i > GT$ where TE_i is the total error of node i and GT is the growth threshold). Grow nodes if is a boundary node. Distribute weights to neighbors if i is a non-boundary node.

6. Initialize the new node weight vectors to match the neighboring node weights.

7. Initialize the learning rate) LR to its starting value.

8. Repeat steps 2 – 7 until all inputs have been presented and node growth is reduced to a minimum level.

Smoothing phase

Reduce learning rate and fix a small starting neighborhood. Find winner and adapt the weights of the winner and neighbors in the same way as in growing phase

4.2.1 Encoding

The trained network is now ready to be used for image compression which, is achieved by dividing or splitting the input images into blocks after that scaling and applying each block to the input of Input Layer (IL) then the out put of Hidden layer HL is quantized and entropy coded to represent the compressed image. Entropy coding is lossless compression that will further squeeze the image; for instance, Huffman coding code be used here. Figure 3 Show the encoding steps

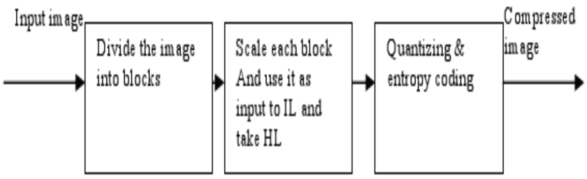

Figure 3 Encoding Process of Image Compression

4.2.2 Decoding

To decompress the image; first decode the entropy coding then apply it to the out put of the hidden layer and get the output of the compressed Image. Figure 4 show the decoder block diagram.

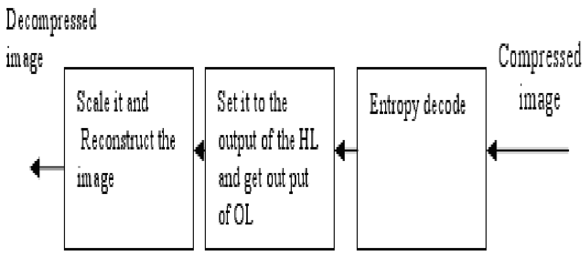

Figure 4. Decoding Process of Image Compression

V. Result Analysis

In order to test the compression engine, several files of various formats were run through the scheme. This system uses three metrics such as compression ratio, transmission time. Compression ratios are defined as [9].

$$Z = \frac{\text{Compressed Length (in bytes)} \times 100}{\text{Total Length (in bytes)}}$$

Compression Ratio = 100 – Z

Table 1 show the compression ratio of various file such as BMP, JPG, TIFE

Table 1. Compression Ratio of BMP, JPG, TIFE file

BMP File Compression			
File Size	**Original byte**	**GSOM Algorithm**	**Compression Ratio**
1.56 MB	1.644,945	1.15 MB	33%
3.84 MB	4.029,002	1.54 MB	60%
6.77 MB	7.7101,066	3.41 MB	77%
JPEG File Compression			
File Size	**Original byte**	**GSOM Algorithm**	**Compression Ratio**
377 KB	386,098	323 KB	65%
508 KB	520.4	377 KB	64%
880 KB	901,213	508 KB	75%
TIFF File Compression			
File Size	**Original byte**	**GSOM Algorithm**	**Compression Ratio**
1.20 MB	1,269,350	926 KB	88%
2.17 MB	2,277,422	1.19 MB	89%
3.66 MB	3,846,382	2.15 MB	75%

The graph for different compression ratio is BMP File Size

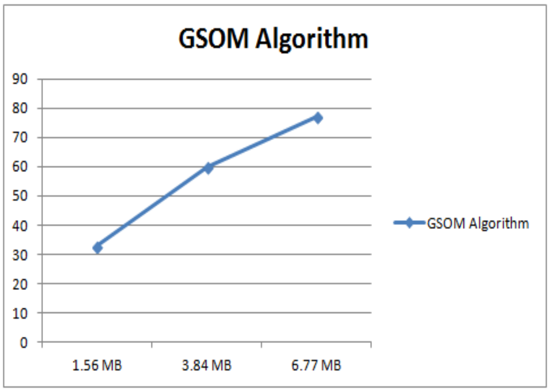

Figure 5: Compression in BMP

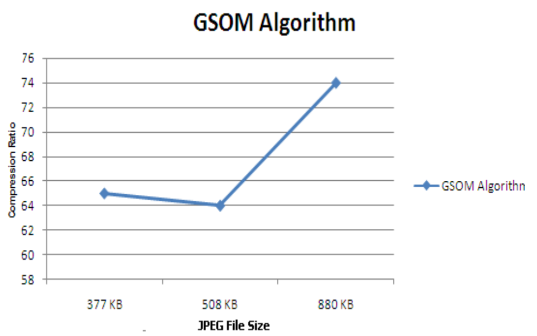

Figure 6: Compression in JPG

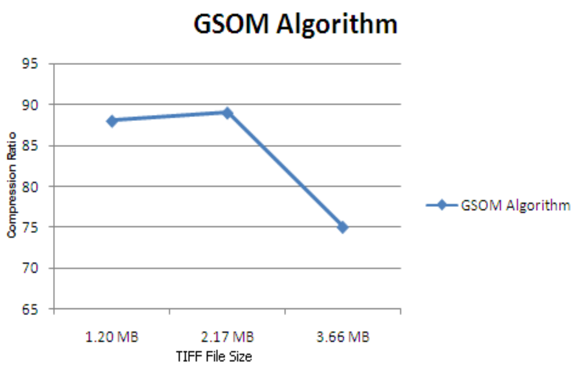

Figure 7: Compression in TIFF

Identifying files as belonging to particular classes offers a quicker way of encoding and decoding the files. The GSOM Algorithm offers us a way of encoding knowledge as a set of training examples rather than by a set of rules and is an effective technique for problem domains where there are many rules or the rules cannot be easily devised. This research also shows that conventional computing and artificial neural networks are not in conflict with each other but each can be exploited for the advantages they offer

VI. Future Enhancement

- Artificial Neural Networks is currently a hot research area in Data compression.
- GSOM algorithm for data compression being a wide field which is rapidly finding use in many applied fields and technologies
- GSOM has some limitation. They can not compress higher size of audio and video file. So To Improve the Compression Ratio of higher size of audio and video file in future enhancement

7. Conclusion

Our main work is focused on the data compression by using Growing Self Organizing Map algorithm, which exhibits a clear-cut idea on application of multilayer perceptron with special features compare to Hoffman code. By using this algorithm we can save more memory space, and in case of web applications transferring of images and download should be fast. The propose approach (Gsom) are used to compressed the various image file such as BMP, JPG, TIFE etc and compression ratio is batter then other traditional algorithm such as Huffman, LZW, Arithmetic etc.

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