Survey on Static Image Storage and Retrieval Mechanisms

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***Abstract*— Many ways of static image storage and retrieval exist. The intent of the work is to explore different methods of image storage and retrieval so that, a different approaches to image storage and retrieval can be devised. Here, the effort has been made to review static image storage and retrieval mechanisms in pursuit of finding out the possibility of formalizing the concept of graded memory as explained in the paper. Few of the memory architectures related to multiresolution are reviewed. The review is mainly focused on works in the area of multiresolution, BAM, wavelets, DCT and fractals**

Keywords*— *Image storage, image retrieval, multiresolution techniques

I. Introduction

Recent trends show that many applications use information in the form of image requiring one to store this information on a storage device in some form. Websites related to social media, multimedia applications on computers and mobile platform generally require storage of large number of images Also, security applications starting from monitoring or surveillance of a store to any large office that requires huge amount of picture/video information to be stored.

Currently, picture/video images in such cases are stored in compressed form using compression techniques like JPEG/MPEG4 etc. Even with this, the memory requirement is huge. The memory used in all these cases is lossless meaning that the image retrieved from the memory is exactly same as the original image.

Generally, many applications do not need high resolution picture/video to arrive at a conclusion. In these cases, the memory need not be lossless and may be lossy, i.e., the retrieved image may not exactly match pixel to pixel. The lossy image is sufficient in many situations to arrive at some conclusion.

If the situation warrants, one can ask for the picture/video with higher resolution, The details of multiresolution transmission and reception can be found in [54, 55]. This multi resolution property is used in graded memory, where, the image quality in a stored image increases with lapse of time, if one can afford to wait for sufficiently long time. Compact storage and online generation of the multi resolution components are the essence of this concept. The proposed work is mainly related to multi resolution image recall, so, literature related to multiresolution has been reviewed.

In evaluating the feasibility of the concept of graded memory, the literature review is carried out focusing mainly on currently available multi-resolution image storage and retrieval mechanisms, the kind of the logic to be used like the use of compression techniques such as JPEG, wavelet and fractal [56], bidirectional associative memories (BAM), neural networks, neuron processors.

II. BACKGROUND

Theory of multi-resolution decomposition of an image using wavelets as presented in [1][2] explains the decomposition of image into multiple approximations which can be called as wavelet coefficients, with each approximation at certain level of resolution. To reconstruct the original image all these wavelet coefficients are required. If while reconstructing, any coefficients are not taken into account, the reconstructed image will not exactly match the original image.

Overview of different types of multiresolution approaches is presented in [3]. Where, Features of images can be filtered and extracted using Gaussian filter which basically smoothens or blurs an image. Two techniques under Gaussian multiresolution namely, the space scale representation and the pyramidal representation are presented. Space scale representation keeps the size of the image constant at different levels of resolution of the image whereas, the pyramidal representation halves the size of the image at each lower levels of resolution. The laplacian filter is used to detect the edges of the image. With the construction of laplacian pyramid, edges can be detected at multiresolution. Among the different ways of construction of laplacian pyramid presented, the one which involves computing at each level the difference of two consecutive Gaussian levels. Also, since the sizes of the two levels of the Gaussian pyramid are different, sizes of the two consecutive levels are made equal by expanding the size of the smaller image to equal to that of the larger image. These pyramids mainly are not guided by the content of the image. To overcome this problem, stochastic pyramid and adaptive pyramids are used. Stochastic pyramid uses Similarity graph showing the similarity between the adjacent pixels and the adjacency graph representing the interconnections among the pixels. Adaptive pyramid does not use similarity graph.

A procedure to split any natural image into a collection of successive and independent levels of resolution is presented in [4]. To decompose an image, wavelet filters defined by the non Gaussian statistical properties of the natural image are used. This only provides a starting point and does not talk about more realistic visual filters. The procedure provided can be applied to decompose only natural images. Also, the spatial correlations at a particular level are short-ranged. The algorithm for the procedure as explained in [4] is presented in [5]. Multiresolution representation of images using wavelets as presented in [6] uses dilations as well as translations of autocorrelation functions.

Detailed theory on nonlinear multiresolution Signal decomposition schemes using morphological pyramids and morphological wavelets are presented in [7] and [8].

An evaluation of multiresolution storage for sensor networks is presented in [9], which uses in-network wavelet based summarization. Several aging strategies in the form of algorithms like omniscient algorithm, greedy algorithm and training-based algorithms are provided. The analysis of the performance of these algorithms shows that the training algorithm performs better than the other two algorithms.

Image fusion is the process of combining the useful information from two images to get an image which is better than the two input images. Multiresolution based image fusion is presented in [10] using additive wavelet decomposition. Here, a technique for efficient image fusion is presented which adds the high resolution image wavelet coefficients to the low resolution multispectral image. Different methods to carryout image fusion using above concept is studied. The method gives better results compared to already existing intensity-hue-saturation mergers. The method uses “trous” algorithm.

A new scheme was proposed in [11] which shows how a directional multiresolution image representation using contourlet transform. Two approaches for dealing with piecewise smooth image, curvelet construction and contourlet construction are presented. It also, provides basic insights on how contourlets can be applied in other signal processing applications. The multiresolution property of the wavelets has been used in [12] clustering of large databases which spatial in nature. They demonstrate identifying clusters of some predefined shapes at various levels of resolution with varying degree of accuracy.

III. COMPRESSION TECHNIQUES

There are many compression techniques that can be used to compress static images. Here, the review focuses mainly on use of DCT, Wavelet transforms and fractals in image compression. Discrete wavelet transform is extensively applied in signal processing and especially in image processing for performing operations like image compression, interpolation etc. The work presented in [13], applies wavelet transform for image interpolation to resize an image. The 5/3 lifting scheme is used to design wavelets and perform discrete wavelet transform. Using DWT normally to resize an image puts restriction on the resize of the image as DWT divides the original image size into exactly half both horizontally and vertically. This problem is overcome in [14], where the concept of zeroth level DWT and Fractional level DWT is introduced which help in resizing the image to any size not exactly divisible by 2n where, n is an integer. This helps one to resize the original image to any size either bigger or smaller than the original image. The paper also presents an algorithm to perform variable scale interpolation.

The work proposed in [15] compares various interpolation techniques with that being done using DWT. The performance of different interpolation techniques like Bilinear, Bspline combined with the use of different filters like Coif 22_14, MS10_10, TVC10_18, VBL6_10, Brazil 6_6 are compared. The results show that interpolation done using DWT with the filters Coif22_14,MS10_10 and TVC10_18 filters gives better results than VBL6_10 and Brazil6_6 filters.

The comparative performance analysis of using DCT and wavelet transform in image and video coding is presented in [16]. It is observed that wavelet coding is better for still images by atmost 1 db of PSNR whereas, the performance of DCT and wavelet transform in video coding is almost equal. The study also concludes with the note that only optimizing the transform used in the algorithm is not enough, quantization and entropy coding also play an equal role in arriving at efficient image and video coding.

The image compression using discrete cosine transform [17] provides basics of image compression using DCT. The high quality discrete cosine transform (DCT) based image compression method is presented in [18] which combines advantages of several approaches. The method divides the image into blocks of different sizes by using rate-distortion-based horizontal-vertical partition scheme. It also uses bit-plane dynamical arithmetic coding for reducing the statistical redundancy of quantized DCT coefficient of each image block. The method proposed yields better PSNR value (an increase in approximately 1 db) for the same level of compression compared to JPEG, JPEG 2000, SPIHT and other wavelet based image compression techniques.

Normally, JPEG gives better compression ratio. The image compression technique presented in [19] using singular value decomposition (SVD) process yields around 65% better compression on top of the compression ratio achieved by standard JPEG image compression technique. The details of how to get singular value decomposition of a matrix is best illustrated in [20] providing step by step approach in finding SVD for a given matrix of size mxn. Application of SVD in digital image processing is presented in [21] explains how SVD can be applied to image compression with an example of face recognition problem.

IV. BIDERECTIONAL ASSOCIATIVE MEMORY

Neural networks can be used for all the applications requiring intelligence. Some of the applications of neural networks [88] are they can be used as auto-associative, hetero-associative memories apart from various other applications. Bidirectional associative memory (BAM) is the minimal two layer neural network with nonlinear feedback connections. BAM’s are extensively used in pattern association. As shown in the figure 1, the information passes from one neuron field to the other through the connection matrix W, whereas, the information passes in the backward direction through matrix WT which is the transpose of matrix W The work presented in [22] shows that by introducing bidirectionality in the neural network, forward and backward associative search for stored patterns extends the symmetric unidirectional auto associators [23] of Cohen and Grossberg [24] and Hopfield[25][61]. The proof of the BAM concept is extended to continuous and adaptive BAM's. Figure 1 shows the BAM in it's simplest form.

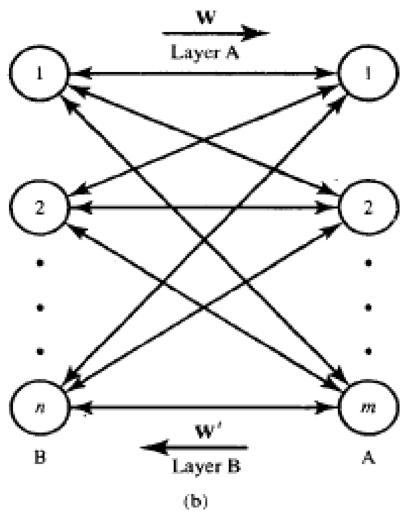

Fig. 1. Bidirectional Associative Memory

Feed forward bidirectional associative memory was proposed in [70], that uses on shot design algorithm. Jooyoung Park et al. [63] have proposed design procedures and derived theorems for Asymmetric BAM model that stores a bipolar vector pairs with error correction properties. The modeling of associative memories using neural networks usually deals with storage and retrieval of images in the form of binary or bipolar patterns. The exhaustive analysis of gray scale auto associative morphological memories [26] is carried out using min-max algebra. The modified gray-scale auto associative morphological memory (AMM) model os presented which associates and image pattern which is closest to the input image pattern with respect to the chebyshev distance. It also explains how MAM's can be used as image classifiers.

The evaluation of Segmentation based Fractal Texture Analysis (SFTA) which is a new algorithm developed to extract features of the image is presented in [27]. This algorithm can be applied to general images as well as medical images. They also present two threshold binary decomposition algorithm which is used by SFTA to partition the grayscale input image into a set of binary images used to characterize textural patterns. SFTA performs better than Gabor and Haralick when applied for image classification and content based image retrieval.

Analytical models for tumor detection using multiresolution fractal feature extraction formalized in [28]. It assumes that tumors in medical images have a fractal (self-similar) growth behavior. A review of mathematical methods, tools available for preprocessing and analyzing the remote sensing generally received from satellite is presented in [29]. A new method of 2D coding based on L-systems fractal hypothesis with better security and capacity for coding in presented in [30]. It uses the shapes of fractal curves in defining the 2D codes. These fractal codes are stored in the Hopfield neural network. The Hopfield network decodes these fractal codes by recognizing the lines. As the technology advances in the satellite development, satellites sends very high resolution images conveying information about certain part of the earth, which is area of interest. It becomes difficult to use and analyze such a high resolution image data due to heterogeneity of the objects displayed in the image. To overcome this, a new approach is proposed in [31] which make use of multi-fractal formalism for image compression. It addresses the problem of edge preserving smoothing of high-resolution satellite images. It involves a pre-processing step for feature extraction and/or image segmentation.. This process consists in smoothing heterogeneous areas while preserving the main edges of the image.

Multiresolution associative memory (MAM) structure is proposed in [36] to overcome the memory requirement (exponentially dependent on the input dimension) problem in the case of lattice based associative memory. A fuzzy rule based system is also proposed as a method to implement the heuristic that is at the heart of the MAM network's training algorithm. The paper [37] surveys existing multi resolution modeling techniques and speculates about what might be possible in the future. The work proposed in [38] is related to development of super resolution algorithm on SOC. This is a low cost/real time algorithm.

The work proposed in [42] presents a fast multi-resolution block-matching algorithm (BMA) using multiple motion vector (MV) candidates and spatial correlation in MV fields, called a multi-resolution motion search algorithm (MRMCS). The proposed MRMCS satisfies high estimation performance and efficient LSI implementation.

The work proposed in [43] introduces a neuro-associative approach to recognition which can both learn and identify an object from low resolution low-quality video sequences. A fast computation method of the normalized correlation for multiple rotated templates by using multi resolution Eigen images is proposed in [45]. This method allows us to accurately detect both location and orientation of the object in a scene at faster rate than applying conventional template matching to the rotated object.

Few of the memory architectures have been proposed, the work proposed in [49] talks about a real-time multi-core object recognition processor having Visual image processing random access memory (VIP-RAM). The work [50] presents an SVC decoder architecture supporting spatial and coarse-grained quality scalability.

The work [51] proposes a Video Compression Architectures for Mobile Communication, The work proposed in [53] provides Theoretical and Mathematical Models for Visual Information Processing in the Brain. The proposed work in [57] details how an image can be compressed using only fractal and wavelet-fractal technique.

The work presented in [57] uses a neuro-associative network to recognition which can both learn and identify an object from low-resolution low-quality video sequences. The approach is derived from a mathematical model of biological visual memory, in which correlation-based projection learning is used to memorize a face from a video sequence and attractor-based association is performed to recognize a face over several video frames.

Many methods have been proposed in the area of binary associative memories. Gray-scale Image recall from Hopfield multilayer neural network by providing noisy image is presented in [32]. The algorithm and digital implementation of the algorithm to carry out image recall is provided in [33]. The multilayer Hopfield network with intra layer connections only for recalling an image is presented in [34]. All these works mainly target at recalling an image by providing a noisy version of the image.

The method presented in [34] decomposes the image into L binary patterns. Each pattern represents one bit in a digital coding of the gray levels. The image is stored independently using a conventional neural binary network with n neurons, where n is the number of pixels. There are L uncoupled neural networks with n2 connections in each level. The main advantage is that L uncoupled neural networks can be implemented in parallel saving considerable amount of time during both training as well as recall In this method, if a binary pattern cannot be stored in one sub-network, then the whole image cannot be stored. Same thing applies to image recall. Similar problem exist in case of [35] when large scale image is decomposed into many sub-images stored in independent neural networks. Overlapping between sub-images[82] is done to overcome these effect.

The work [59] proposes a method to store an integer value as a fixed point in a complex valued multistate Hopfield network. This method is based on a set of linear inequalities. The work [60] proposes use of single layer continuous Hopfield network for gray scale image storage and retrieval. The stored images are recalled when the noisy images with salt and pepper noise of arbitrary density are presented to the network. The network uses nonlinear coupling. The work [62] proposes grayscale image storage that combines complex valued associative memory (CAM) and 2-D discrete Fourier transform. The input images are transformed to quantized phase matrices. Each neuron in the network is complex valued with the value of each neuron corresponding to the elements of the matrix. The number of neurons required to store an image is reduced by neglecting or removing high frequency components of the quantized phase matrix. This will degrade the image quality.

Stanislaw Jankowski et al, [64] have proposed a neural associative memory with each neuron state can be one of 2L complex values, on the unit circle. A particular phase corresponds to a gray level. The network is fully connected. For network with n neurons, the number of connections is equal to n2. They have demonstrated that gray-scale images can be stored and recalled using such network as long as the phase shift between gray pattern components is maintained. A general Hebbian rule for complex valued neural networks is proposed in [64,65]. All these have similar limitations, whereas [66] proposes a weigh matrix design using set of linear inequalities.

The two-dimensional cellular neural network (CNN) is of size MxN where, M is is the number of rows and N is the number of columns. C(i,j) represents a cell located at ith row and jth column. The detailed theory on cellular neural networks is presented in [79]. The work [67,68] propose neural networks consisting of multi level states for each neuron. The activation function has 2L plateaus instead of two as in normal signmoid function. Each state of the multi-valued states of the neuron corresponds to the gray levels. The extensive details on how to generalize fully connected Hopfield neural network is presented in [69]. This is done by replacing bi-level activation function with multi level activation functions. It has been shown that activation function having N+1levels gives N+1 minima and N saddle points.

Use of discrete cellular neural networks as associative memory is presented in [71] by adapting Hebbian rule as the memory design rule. Detailed discussion of memory capacity and other issues like the size of the attracting basi and presented.

To solve a given problem having set of constraints in real time, the design of Hopfield associative memory is reformulated in [72]. The design of associative memory using space varying cellular neural networks is presented in [73] where the connections within the network is based on the nearest neighborhood concept, meaning a neuron will have connections to nearby neurons only as dictated by some parameter like radius. Analysis and synthesis of sparsely interconnected neural network as presented in [74] discusses the design procedure to design associative memories as applied to cellular neural networks. It is shown that the network is able to store patterns due to feedback connections existing the neural network. The synthesis procedure for Brain-State-in-a-Box neural networks is presented in [75]. To guarantee the absence of binary equilibrium points and non binary asymptotically stable equilibrium points near ta desired memory vector, sufficient conditions are derived. The work [77] proposes a fast algorithm to find the connection weights of cellular neural network as applied to associative memory. The learning algorithm presented in [78] has two operating modes, learning mode and recall mode. In the learning mode, there is no feedback and the CNN outputs are used to modify the connection weights. In recall mode, the weights found during learning mode are used as feedback operators and there is no input. The capacity of the associative memory to storing number of prototypes is estimated in [81] and they have found out that the capacity of the CNN to store number of prototypes depends on the connections of the neuron to it's neighborhood, i.e. , the number of neurons to which a particular neuron is connected with valid weights. Use of non-linear switched capacitor for realizing neural networks to solve optimization problems is presented in [80].

There are many works related to image compression using fractals in the literature. The work proposed in [83] explains how to generate a most singular manifold of an image and reconstruct an image using its most singular manifold (MSM). The fractal compression theory and how to decompose an image using fractals is presented in works presented in [83-87].

V. NEURON PROCESSORS

There are many neuron processors that are available in the market. To name a few, Echelon Neuron 5000 processor [89], Cypress CY7C53150, CY7C53120 [90], Toshiba Neuron Chip- TMPN3150/3120 [91].

VI. SUMMARY

After reviewing the literature, it is found that, most of the work that is presented in the literature is in the area of static image storage and retrieval using neural networks namely, Hopfield, cellular neural networks. All these works are mainly targeted at retrieving stored image in the neural network when a noisy version of the original image is presented. We are proposing a graded memory structure using multilayer Hopfield neural network which will work as a human memory. We show that the multilayer Hopfield neural network can be used as a memory in which the output becomes better and better over the period of time when the input image is the down sampled version of the stored image.

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