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Edge Preserving Image Compressor (EPIC) in Medical Image Using Dynamic Associative Neural Networks

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Abstract

Telemedicine is the method which uses digital technology for practitioners to medical diagnosis fast treatment of patient's and use of knowledge in research work. But at the same time it increases the challenge to store, transmission high resolution and big size DICOM images. To reduce the size it should be compressed before transmission and store over the network and use the method to maintain the image quality in restoration of image because the each and every bit information can change the diagnosis method. To achieve this compression number of amalgamated technology developed in recent years. Artificial Neural Network techniques are to accomplish high quality image restoration of medical image. To achieve execution augmentation with respect to compression ratio and deciphered image quality is developed using Edge Preserving Image Compressor with Dynamic Associative of Back propagation networks for image compression. Artificial neural network compression techniques rooted on Dynamic Associative Neural Networks (DANN), to achieve high compression quality restoration in an Edge Preserving Image Compressor well-suited to parallel implementations.

Keywords: Telemedicine, image compression, Artificial neural networks (ANN), Back propagation, compression, and decompression.

Introduction

The increasing adoption of information systems in healthcare has led to a scenario where patient information security is being regarded as a critical issue. Allowing patient information to be in jeopardy may lead to irreparable damage, physically, morally and socially to the patient, potentially shaking the credibility of the healthcare institution. This demands adoption of security mechanisms to assure information integrity and authenticity. Structured descriptions attached to medical image series conforming to the DICOM standard make possible to fit the collections of existing digitized images into an educational and research framework. The major issue that arises in telemedicine is that the problem of sending massive volume of medical information with comparatively low information measure. Recent compression techniques have magnified the viability by reducing the information measure demand and permitting cost-efficient delivery of medical pictures for primary designation. One of the most challenges of these medical imaging systems is addressing massive amounts of knowledge non heritable by the trendy modalities and maintaining the integrity of Medical pictures at identical time. Indeed, new modalities will generate massive amounts of high-quality pictures during a short time. In fact, one in all the foremost necessary demands toward addressing great amount of information is to supply the simplest way for quick data transmission between medical imaging applications. The foremost common approach toward enhancing the speed of knowledge transmission is exploitation compression techniques [5]. Medical images should be subjected to loss-less compression, a technique that stems from mathematical theory of communication (Shannon, 1948**)** and use variable length codes, proposed by Huffman (David Huffman, 1952).To achieve good compression ratio in addition to Huffman encoding, Run length encoding is used[5]. An effective compression technique results in a reduction in storage space, thereby improving the bandwidth and speed of transmission of medical images with no added complexity and resources [4].

Our aim is to style associate degree application to produce lossless compression of Medical pictures by applying Edge Preserving Image mechanical device (EPIC) and run-length encoding[1][5]. This helps in higher information measure utilization of the networks. At an equivalent time, conjointly aims at providing the protection mechanism for Medical pictures by removing the matter parts of the medical image.

Background

With the DICOM normal, it's straightforward to eliminate matter data like patient name and ID. However for digitized films or previous history pictures, a processed detection and elimination formula is required. The matter of text identification arises in several applications apart from medical security. However, the algorithms utilized in such systems aren't designed to handle superimposed text as a result of its troublesome to differentiate the sides of text from the sides of the medical objects within the image. The security filtering method in our system consists of associate economical and correct formula to tell apart areas with and while not matter data in digital or digitized medical pictures. Areas with text will then be blurred or stripy. as a result of variations within the diagonal directions will be found in the majority Roman characters or Arabic numbers, we tend to use Daubechie's wavelets and analysis techniques to find the high frequency variation within the diagonal direction that's indicative of text. A mask is employed to preserve the losslessness of non-textual areas. With some basic information of the machine accustomed produce the image, we tend to area unit able to eliminate solely sensitive patient identification data whereas retentive the medical data within the image. Excellent results are obtained in experiments employing a massive set of real world medical pictures several with superimposed text.

Dynamic associative neural networks based adaptive compression methods which overcome the traditional drawbacks associated with back-propagation based neural networks, such as the static nature of network architectures, unbalanced errors of individual training patterns, and being trapped in local minima during training, have been developed [2][3]. This new neural network architecture, termed Dynamic Auto associative Neural Networks (DANN) has been shown to provide excellent control over the error rates while

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maintaining user-selectable compression ratios.

Dynamic Associative Neural Networks (DANN) have been used effectively for image compression [2][3]. Consequently EPIC utilizes DANN-based neural networks for compressing the non-edge image. However, DANN training suffers from the problem of slow convergence, since the descending epsilon training technique [1] is a very slow process. There are often specific input patterns that are considered very difficult to learn. The single network used for DANN compression to compress all possible input patterns therefore has to account for those difficult patterns in its learning process as well. This further increases the required network capacity and complicates the learning process since the network often has to adapt to input patterns with very different characteristics. All these factors limit the ability to extend DANN-based compression techniques to provide very high data compression ratios while providing very low error rates for use with application where data fidelity is extremely important. EPIC improves upon DANN-based compression through the following features:

i) The use of a bank of DANN networks in place of a single network for processing the incoming data stream, under the control of a variance classifier.

ii) Improvements in the training set generation procedure through the elimination of duplicate training vectors which are close together in Euclidean space, controlled by the use of a similarity threshold.

iii) Improvements in the training process, by specifying termination criteria for pathological training conditions, where the network error is increasing continually or is stuck for a given number of training epochs.

The changes to DANN architectures and training algorithms are detailed in the following sections.

Modified DANN Training Procedure

The neural network training algorithm used in EPIC is based on the DANN training procedure outlined in. Each neural network in the bank of P networks is subjected to DANN training, with some modifications designed to detect pathological conditions and reduce time spent in unproductive training. Among the improvements are convergence detection primitives, which measure the slope of the error curve to determine if the training process is stuck (wobbling) or if the error function is increasing as training proceeds (increasing error). Thresholds are set for the number of iterations the network can exist in these conditions before that particular phase of training is aborted and control returned to the calling routine. The EPIC training process for each of the P networks can be done in parallel, decreasing the time required for learning a given set of images compared to the original DANN training process.

Edge Preserving Image Compressor (EPIC)

The proposed Edge Preserving Image Compressor (EPIC) architecture is a new hybrid image compression technique combining conventional techniques with DANN-based neural networks. EPIC utilizes techniques that are similar to the approach of the edge/non-edge compression algorithm proposed in [1], which in turn is derived from the synthetic-highs compression technique. However, instead of the adaptive DCT compression used for the non-edge image as is done in [3], neural network based compression is utilized, and the edge-subtraction step is eliminated entirely. It is designed to be modular in nature, and improvements in each module can be incorporated easily into the architecture, resulting in better accuracy and performance of the system. One of the major criteria of this architecture is the preservation of edge information of the original image. Since edge detection is a vital step in any image processing and manipulation task, the inclusion of this step into the image compression architecture results in two distinct advantages: the elimination of the need for edge detection in subsequent downstream processing of the images, and the guarantee that edge information is not lost during compression, unlike many transform-based methods. The edge information extraction is useful for other reasons as well. Correlation of anatomical features between images obtained using different modalities is vital for various diagnostic functions involving tissue identification, classification, and metabolic modeling. For instance, CT and MRI image features are used to localize anatomical features obtained from PET and other modalities with less distinct image features and boundaries. The Canny filter produces very clean edges without the need for noise removal and is used by EPIC to perform the edge extraction step during the compression phase. A classifier network examines each block of the image and determines which of a bank of neural nets previously trained is best suited for the compression task using a simple variance classifier. The ability of the neural network to generalize and be trained to adapt to specific types of patterns in the input image is expected to yield better compression ratios and image fidelity as compared to compression using conventional DCT techniques, and is inherently more parallelizable in hardware implementations due to its uniform structure and simple processing requirements. The neural network architecture utilized in EPIC is a multi-layered Perceptron network with two hidden layers, which has been used successfully for image data compression in. The input vector is compressed into a neural network pattern representation using a compression ratio dictated by the ratio between the number of input neurons (equal to the number of pixels in the image block) and the number of neurons in the second hidden layer. The compressed pattern outputs from the neural network compressor is then coded using either a variable bit-rate linear predictive coder, or quantized using a fixed bit-rate with marginally higher distortion. Optional Lempel-Ziv-Welch (LZW) encoding [1]is applied to the outputs of both the edge coding and neural network compressors to remove any residual redundancies. These patterns are then stored or transmitted for use in reconstructing the images at the decompressor.

The decompressor performs the corresponding optional LZW decoding on the received edges and compressed patterns, as well as corresponding linear predictive decoding on the compressed patterns (if required), and passes it through a bank of neural networks which converts the compressed patterns into recovered output blocks that are used to form the non-edge image. This non-edge image is then overlaid with the decoded edge pixels to reconstruct the reconstructed image.

DICOM medical image compression means minimizing the size in bytes of a graphics file without degrading the quality of the

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image to an unacceptable level. The reduction in DICOM size allows more images to be stored in a given amount of disk more memory space. It also reduces the time required for image to be sent over the internet or downloaded from web pages. The recent growth of DICOM image data intensive based web application have not only sustained the need for more efficient ways to encode signals and images but have made compression of such signal central to storage and communication technology. In the present research work Edge Preserving Image Compressor using back propagation neural network training algorithm has been used. The neural network model has been trained and tested for the different types of DICOM images. Back propagation neural network algorithm helps to increase the performance of the system and to decrease the convergence time for the training of the neural network. The aim of this work is to develop an edge preserving image compressing technique using four hidden layer feed forward neural network of which the neurons are determined adaptively.

Neural Network

A neural network is a powerful data modeling tool that is able to capture and represent complex input/output relationships. The motivation for the development of neural network technology stemmed from the desire to develop an artificial system that could perform "intelligent" tasks similar to those performed by the human brain. Neural networks resemble the human brain in the following two ways.

• A neural network acquires knowledge through learning.

• A neural network's knowledge is stored within inter neuron connection strengths known as synaptic weights.

Introduction to Back Propagation

Back propagation is a form of supervised learning for multi layer nets, also known as the generalized delta rule. Error data at the output layer is back propagated to earlier ones, allowing incoming weights to these layers to be updated. It is most often used as training algorithm in current neural network applications. The speed and accuracy of the learning process-that is, the process of updating the weights also depends on a factor, known as the learning rate. Before starting the back propagation learning process, we need the

Following:

- Take the set of training patterns, input, and target.
- Optimum value for the learning rate.
- A criterion that terminates the algorithm and updates the weights using suitable methodology.
- The sigmoid function (for nonlinearity).
- Initial weight values (typically small random values).

Multi-Layer neural networks with back-propagation algorithm can directly be applied to image compression. The simplest neural network structure for this purpose is illustrated in Fig. 1.

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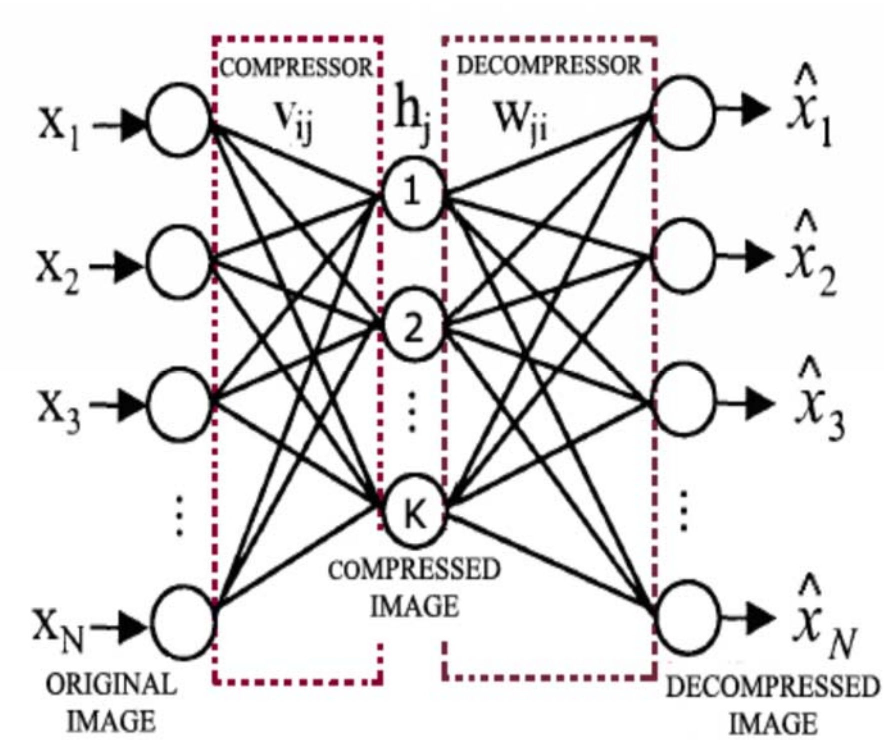

Fig. 1 DICOM image compression structure using neural network

Training

Like all other training processes, in this phase a set of image samples are selected to train the network via the back propagation learning rule. For compression purpose the target pattern in the output layer neurons of the network will be same as the input pattern. The compression is represented by the hidden layer which is equivalent to compress the input into a narrow channel. Training samples of blocks are converted into vectors and then normalized from their gray-level range into [5].

Proposed System Architecture

The functional description of the proposed block diagram (Fig. 2) is as follows

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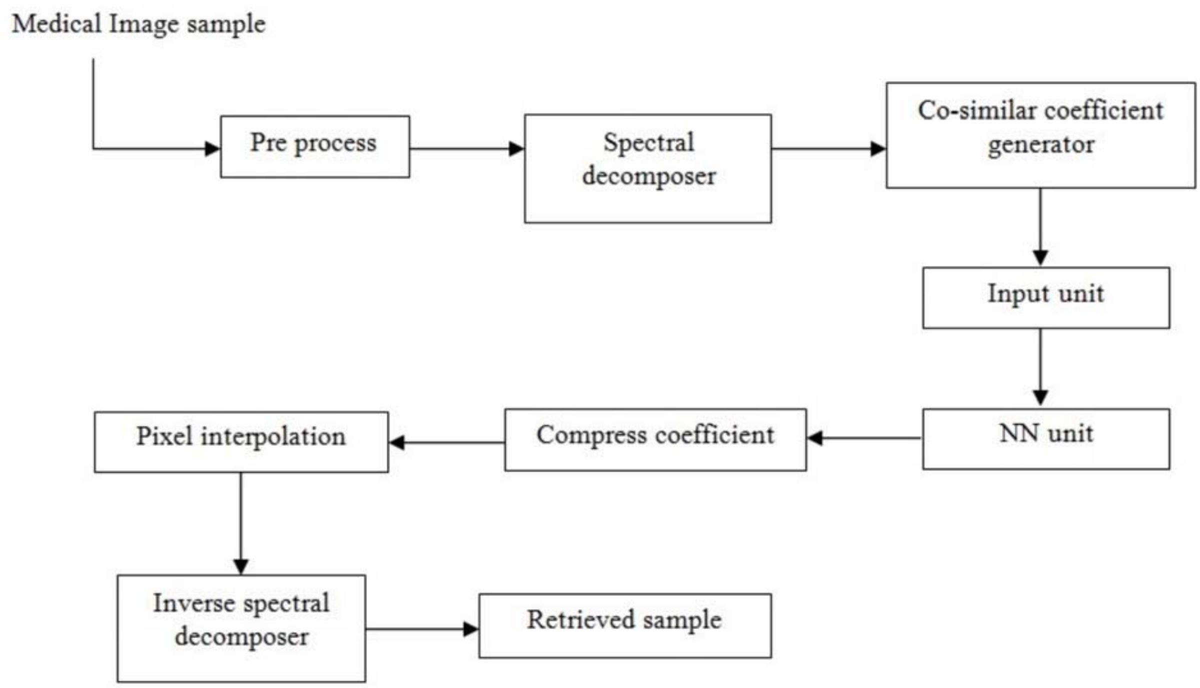

Fig. 2. Proposed block diagram

Pre process unit:

This unit reads the medical sample and extracts the gray pixel intensity for processing. The read samples are passed as pixel array as output of this block and passed for decomposition in spectral decompose unit.

Spectral decomposer unit

This unit reads the gray coefficients and performs a pyramidical decomposition to extract the spectral resolutions for given input sample. The decomposition structured is a 2 dimensional recursive filter bank units, performing DWT operation. The recursive operation is carried out by the recursive filtration using pairs of successive high and low pass filter.

Co-similar coefficient generator unit:

For the obtained coefficient after spectral decomposition, the coefficients which reflect similar spectral coefficients are segregated, these coefficients are called redundant pixel in the image. The suppression of co-similar coefficient results in first level compression based on redundant information. For the obtained co-similar coefficients a neural network modelling is developed.

Input unit:

This unit reads the selected coefficient and normalizes the coefficients to pass to neural network. The unit extracts the coefficient in a column wise manner and is normalized to maximum pixel value.

NN unit:

This unit realizes a feed forward neural network using the command ‘newff’ in matlab tool. The NN unit extract the min-max value of given input and creates a feed forward neural network taking least mean learning algorithm. A tangential sigmoid driving function is used as a kernel function for creating this network. The network is created for converging to the error with a goal of 0.1 and with number of epochs=50. The created network is trained with these coefficient values based on the given input and the created feed forward network.

Compress coefficient:

The coded coefficient after the neural network process is stored into a buffer called compressed coefficient. This formulates an array logic wherein the coded output of the NN is stored for future usage.

Pixel interpolation

The compressed data is processed back in this unit. Wherein the simulated result of the created neural network is normalized back to its original scale based on the obtained simulated output of the neural network. The retrieved pixel coefficients are rearranged depending on the sequence order as obtained from the encoding side.

Inverse spectral decomposer

The coefficient obtained from the above units is processed back, where the coefficients are passed back as resolution information to successive high and low pass filter. The recursive output of each level of filtration is added to the other level filtration result and is recursively filtered to obtain final retrieved level.

Conclusion

The implementation of back propagation neural network algorithm on image compression system with good performance has been demonstrated. The back propagation neural network has been trained and tested for the analysis of different images. It has been observed that the convergence time for the training of back propagation neural network is very faster. Different attributes of compression such as compression ratio, peak signal to noise ratio, bits per pixel are calculated.

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