Management of an Enhancing Focus of Breast Magnetic Hybrid Method For Compressing 3D Head

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Abstract

This research work presents a method for compressing a Magnetic Resonance Image (MRI) that is used for the medical diagnosis, of a patient in modern healthcare systems. More effort has been given for the region of interest, so that transmission time as well as bandwidth shall be reduced. This leads to the brawny demand for digital medical image compression and consistent transmission. In this study EBCOT with Radial Basis Function Networks (RBFN) is analysed and experiments were carried out and the quality of reconstructed images is evaluated based on performance metrics as Compression Ratio (CR) and Peak Signal to Noise Ratio (PSNR). The results show that higher compression ratio is achieved for RBFN while maintaining image quality and preserving the information. In this work there is no loss of data in the preprocessing and hence the finer details in the image are preserved in the reconstructed image.

Introduction

With the advance development in technology, medical field has been significantly benefited and novel opportunities for researches opened up, one such turf being the real time medical image processing whose applications have allowed medical practitioners global to better diagnosis abilities. Providing health care services in rustic areas is an exigent task that may be applied using telemedicine applications. Electronic means of communication provides major improvement in health care services in the declared areas of telemedicine. Rapid Internet development in recent years has been made telemedicine in a drastic way towards medical applications. Hefty medical centers can be connected with rural areas through telemedicine which helps to exchange medical information between distant locations.

A massive amount of space is required for digital images to store the data and for transmission with large bandwidth. The target of image compression is to reduce the amount of data required to represent as well as remove to store a digital image. Nowadays, Picture Archiving and Communication Systems (PACS) shall allow image compression to reduce the size of data on their storage requirements for all kinds of application. Medical image compression plays a imperative role in hospitals to maintain relevant diagnostic information of a patient.

As we need to compress enormous amount of data on each day, it is very essential to go in-depth research on image compression. Tele-radiology sites are benefited since reduced image file sizes yield reduced transmission times (Zukoski M J 2006) Today, technologies have been grown in such a way that there have been various compression research studies for examining the use of medical image compression about images as MRI(Magnetic Resonance Imaging), X-ray and CT(Computed Tomography).

This paper focuses on image compression for the region of interest using modified EBCOT coding with Radial Basis Function Networks. The rest of the paper is organized as below. Section 2 gives a brief discussion of the related work. Section 3, talks about Radial Basis Function Networks. Section 4, describes the methodology used in this paper. Results and discussion have been presented in Section 5. Section 6 concludes with conclusion & future considerations.

2. Description Of Related Work:
The work on image compression performed by various researchers can be found in literature related to neural network based image compression technique. This section of the paper discusses some of the earlier work proposed on image compression using neural networks. (Victor Sanchez et al 2013) proposed a novel 3-D scalable compression method for medical images with optimized volume of
interest (VOI) coding. This particular method can be used for interactive telemedicine applications. At this juncture different remote clients may access the compressed 3-D medical image data stored on a central server. This can be done by the requisition of different VOIs from a lossy to lossless format. Here 3-D integer wavelet transform has been used with modified EBCOT.

Further (Gokturk, et al 2001) performed Medical Image Compression Based on Region of Interest, for Colon CT Images. Hybrid model of lossless compression in the region of interest, and lossy compression in other region was introduced here. This method on medical CT images outperforms other common compression schemes, such as discrete cosine transform, vector quantization, and principal component analysis. This method gives the compression rate of 2.5%.

3. Radial Basis Function Networks (RBFN):
Radial basis function networks are also feed forward, with only one hidden layer. Radial basis function networks are feed-forward networks trained using a supervised training algorithm. A single hidden layer is used to configure the network. The output function of this hidden layer is selected from a class of functions called basis functions. This work deals with three types of basis function namely Gaussian Radial basis function, Multi quadrics Radial basis function and Inverse multi quadrics Radial basis function are used for compression. Each functions are defined by the following equations. The Gaussian Radial basis function is the one which is mostly used among the three and is shown in figure 1.

\[
\phi (r) = \exp \left(-\frac{(r^2 + c^2)}{2\sigma^2}\right)
\]

Gaussian Radial basis function

Where \( \phi (r) \) and \( r \) are shown in figure 1. This function \( \phi (r) \) responds only to a tiny area of the input space where the Gaussian is centered which can be done with supervised learning. In general the formation of an RBF network involves three utterly different layers as shown in figure 2. The Structure of a standard Radial Basis Function Network is shown in figure 2.

Here the input layer is made up of source nodes whose number is equal to the dimension N of the input vector. The second layer is the hidden layer which is composed of nonlinear units which are directly connected to all of the nodes in the input layer. Each hidden unit takes its input from all the nodes of the input layer. The hidden unit contains a basis function, which has the parameters at the center width. (Singh A V et al 2010)

4. METHODOLOGY (IMAGE COMPRESSION USING RBFN):
The proposed method contains three different phases namely Preprocessing, Classification and Compression which is given figure 4.

4.1 Image Data:
The real data used in this work are collected from scan centers. The data contain normal as well as abnormal MRI brain images. Proposed method of Compression is done for abnormal images. 50 images of normal and abnormal cases of head MRI have been taken for the analysis. Few slices used here are given in figure 3.

4.2 Image Preprocessing:
This step comprises the conversion of Input image into gray scale image and noise removal. As there is no reduction in contrast across steps this work is engaged with median filter for noise removal (Ramteke R J and Khachane Monali Y 2012)

4.3 Classification:
There is a high variability of the MR medical image. So it is significant to use suitable models in the classification process. In this work medical image is classified as normal and abnormal, which consists of two steps namely Feature Extraction and K-Nearest neighbor (K-NN) algorithm.

4.3.1 Feature Extraction:
This research talks about three features namely Contrast (C), Correlation (Cor), and Entropy (E) for the extraction of an abnormal image and is stored in the database. So that original data set will be reduced for further classification.

4.3.2 K-Nearest Neighbor (K-NN) algorithm
This phase classifies the input test image into Normal and Abnormal Class by using K-Nearest Neighbor algorithm. The Normal Classified image is displayed as the normal image and Abnormal Classified
image is passed to the next phase for compression. In this study, the value of k was chosen as eight after testing with a number of values of k.

4.4 Compression

Compression is achieved with several independent steps namely Separation of VOI & non VOI, EBCOT compression for background (non VOI) image, EBCOT compression with RBFN for Tumor (VOI) image, Transmission of VOI region, Non VOI region for archive purpose.

4.4.1 Separation of VOI & non VOI

Here abnormal image is separated as VOI & non VOI by k-means clustering and segmentation.

4.4.2 EBCOT compression

EBCOT is an entropy coding algorithm for 2-D wavelet transformed images, which generates a bit-stream that is both resolution and quality scalable. In EBCOT the bit-stream of each code-cube may be independently reduced for different lengths, due to the entropy coding (Sanchez v et al 2010) process, this is performed by means of various code passes. After that truncated bit-streams have been converted into a number of quality layers to form a scalable layered bit-stream. This is done by gathering the incremental assistance from various code-cubes into the quality layers such that the code cube contributions result in a rate-distortion optimal representation of the 3-D image, for each and every quality layer.

4.4.3 Algorithm for Region of interest using RBFNN

Step 1: Obtain the input image
Step 2: Normalize each input so that the values lie in between 0-1.
Step 3: Each MRI slice is divided into non-overlapping sub-images. Here 256 x 256 bit image is divided into various pixel sizes like 4 x 4 or 8 x 8 or 16 x 16.
Step 4: The normalized pixel value of the sub-image will be given as the input to all the nodes in the network. Here three-layered Radial Basis Function Network is used to train each sub-image.
Step 5: The number of neurons in the output layer will be the same as that in the input layer.
Step 6: The output of the input layer is evaluated using the transfer function for a radial basis neuron.
Step 7: The hidden layer is computed by multiplying the corresponding weights of synapses. The hidden layer units evaluate the output using the transfer function for a radial basis neuron.
Step 8: The input to the output layer is computed by multiplying the corresponding weights of synapses. The output layer neuron evaluates the output using linear function.
Step 9: The neural network is tested for different MR image slices and the values of PSNR, CR, MAE, NK, MSE, and AD are calculated.

5. Experimental Results And Discussion

This section thrashes out the experimental evaluation of the proposed algorithm based on several experiments which involves real image data. Totally 50 images of normal and abnormal cases of head MRI have been taken for the classification. In which 20 images are normal and 30 images are abnormal, which are separated out. Abnormal cases in the sense, images that are with tumor have been taken for the third step. In 30 abnormal cases, tumor portion is separated out and RBFN with EBCOT compression is applied for the region of interest. The remaining area is compressed with EBCOT coding. Assessment results have been found with the cumulative distribution and without cumulative distribution. Compression ratio as well as the convergence of the network can be improved with cumulative distribution than the other one. Figure 5 shows the various step outputs starting from Original image and the reconstructed image with its intermediate steps. For various epochs experiments are conducted and the MSE value is reduced in an effective manner. Also compression ratio is effectively increased without affecting image quality. The quality of the medical image is measured using objective factors like Mean Square Error (MSE), Peak Signal to Noise ratio (PSNR), compression ratio (CR), mean absolute Error (MAE) and Normalized cross correlation (NK). The parameters MSE and PSNR define the quality of a reconstructed image at the output layer. Usually a lower value of MSE is preferable as because of the reconstructed image quality. In an ideal world, the mean square error should be zero for ideal decompression. For lower values of MSE, compressed signal error performs low [10]. In ANN image compression system, the CR is defined by the ratio of the data fed to the input layer Neurons to the data output from the hidden layer neurons. Experimental Results of the Proposed Approach using Radial Basis Function has been given in table 2. Different methods have been compared with the proposed method in table 2 which shows the proposed method yields good results comparing other methods. PSNR of the Proposed Approach with and without cumulative distribution is discussed in
table 2. From which it is found that PSNR can be improved by adding cumulative distribution. Proposed approach suits well for RBFN with cumulative distribution function than the other one. Relative redundancy \((R_{R})\) & Root mean square error (RMSE) of the Proposed Approach is also calculated and is given in table 3 for Epoch 2000. Generally Compression attempts to redundancy. Here Relative redundancy is used to calculate the redundant information. Relative redundancy of the compressed image is calculated by using following equation:

\[
R_{R} = 1 - \frac{1}{C_{rc}}
\]  

(4)

Where \(C_{rc}\) is the compression ratio.

From table 3 on an average there is 95% of redundant data, which have been avoided using this method. The method is implemented by using MATLAB. The evaluation measurements have shown that this method performs well by 90% comparing other methods for MR images with region of interest. This new method of compression algorithm can be used in teleconsultation to improve the performance of Compressed image (VOI), so that there is no need of transmitting the whole image for consultation. Only affected area can be transmitted which takes minimum transmitting time with its good quality.

**Conclusion**

In this paper, a new image compression scheme which is used to compress medical image based on the modified EBCOT with Radial Basis Function Networks (RBFN) has been proposed. The proposed algorithm is simple and computationally less complex which is based on embedded block coding with coefficient truncation. This method results in efficient compression with reduced computational time and MSE. Also this is superior to EZW, SPIHT, and Modified EZW. In future this work can be extended to real time applications for video compression in medical images.

**References**