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MEDICAL IMAGE COMPRESSION USING NEURAL NETWORK

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ABSTRACT
After the advent of Biofeedback era, the requirement of an effective online processing algorithm for EEG data becomes very vital. In this paper, authors proposed a decent method for real time classification of EEG data for imagination of left hand and right hand movement, based on temporal variation of relative spectral power. The proposed Temporal Relative Spectral Power (TRSP) based algorithm is first and robust unsupervised machine learning algorithm for real time brain computer interface(BCI). The relative spectral power is used as feature. The estimated feature further processed for classification through probabilistic Bayesian classifier. The proposed method of EEG signal processing outperforms the conventional wavelet based BCI competition II results for movement imagery classification.

Keywords: Brain Computer Interface (BCI), Electroencephalogram (EEG), Movement Imagery, Temporal Relative Spectral Power (TRSP) and Wavelet.

INTRODUCTION
All hospitals are adapting digital environment for medical image digitization, processing, storage, and transmission. Our basic motivation is to represent medical images in a digital form to support image transfer and archiving. The stored medical images are manipulated for obtaining diagnostic information in new and more efficient ways, such as image enhancement and 3D volume rendering. In comparison with current analog film-based medical images, digitized images must be of high quality and high resolution and, therefore, require a very large storage space. To represent such large medical images with the smallest possible number of bits, data compression is essential for minimizing storage requirement and speeding transmission across low bandwidth channels. Lossless image compression techniques are used for compressing medical images to ensure its correctness and accurate diagnosis. Data compression schemes for medical images can reduce the volume of data handled and play an important role in the coming use of radiology systems and picture archival and communication systems (PACS) in the near future.

CONVENTIONAL TECHNIQUES FOR IMAGE COMPRESSION
The purpose of medical image compression is to reduce the data volume and to achieve a low bit rate in the digital representation of radiological images without perceived loss of image quality. For still image compression, ISO (International Standards Organization) and IEC International Electro Technical Commission) have established the 'Joint Photographic Experts Group' or JPEG standard. The performance of these coders generally degrades at low bit -rates mainly because of the underlying block-based Discrete Cosine Transform (DCT) scheme. More recently, the wavelet transform provides substantial improvements in image quality at higher compression ratio.

JPEG: DCT- Based Image Coding Standard
In 1992, the Joint Photographic Experts Group (JPEG) established the first international standard for still image compression where the encoders and decoders are Discrete Cosine Transform (DCT)-based. The JPEG standard specifies three modes namely sequential, progressive, and hierarchical for lossy encoding, and one mode of lossless encoding. The DCT–based encoder worked by segmenting the image into 8*8 blocks. Each block makes its way through each processing step, and yields output in compress form into the data stream. As image pixels are highly correlated, the DCT achieves data compression by concentrating most of the signal in the lower spatial frequencies. For a typical 8*8 sample block from a typical source image, most of the spatial

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frequencies have zero or near-zero amplitude and need not be encoded. In principle, the DCT introduces no loss to the source image samples; it transforms them to a domain in which they can be more efficiently encoded.

Wavelet Transform Image Compression

Wavelet transform techniques currently provide the most promising approach to high-quality image compression, which is essential for radiology and Picture Archiving and Communication System (PACS). Wavelet compression was applied to compress and decompress a digitized chest x-ray image at various compression ratios. It involves the use of a new field of applied mathematics often called 'wavelet theory' or simply "wavelets". Wavelet compression is a subset of a larger class of techniques generally referred to as "transform-based compression". The first step in a transform-based technique typically involves a lossless mathematical transform to provide a sparse representation of an input image. The transformed data are then quantized, in order to achieve the desired level of compression. Transform domain values that are quantized can never be restored to their original accuracy, but such quantization is necessary in order to achieve higher compression ratios. The greater the reduction in precision or quantization, the greater the compression ratio and the larger the error introduced into the compressed image. The last step in transform-based compression is often referred to as "entropy coding" and involves the application of standard lossless compression techniques that may include run length encoding (RLE), Huffman coding, or arithmetic encoding. Histogram analysis, maximum absolute error (MAE), mean square error (MSE), root mean square error (RMSE), signal to noise ratio (SNR), and peak signal to noise ratio (PSNR) were used as a set of criteria to determine the 'acceptability' of image compression. The wavelet algorithm was found to have generally lower average error matrices and higher peak signal to noise ratios. Wavelet methods have been shown to have no significant differences in diagnostic accuracy for compression ratios of up to 30:1. Using wavelet algorithm, a very high compression ratio of up to 600:1 is achieved.

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 decoded despite being of variable length. 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.

NEURAL NETWORK METHOD FOR MEDICAL IMAGE COMPRESSION

Artificial Neural Network (ANN) based techniques provide other means for compression of data at the transmitting side and decompression at the receiving side. The security of the data can be obtained along the communication path as it is not in its original form on the communication line. The purpose of this paper is to present the different techniques that may be employed for medical image compression and propose a new technique for better and faster compression. Neural networks seem to be well suited for compression of medical images, as they have an ability to preprocess input patterns to produce simpler patterns with fewer components. 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 neural algorithms like Back propagation algorithm and Kohonen's self-organizing maps algorithm preserves the full information about compressed data (stored in a hidden layer) obtained from the external environment. The compressed features may then exit the network into the external environment in their original uncompressed form.

Backpropagation Neural Network for Image Compression

The Backpropagation (BP) algorithm has been one of the most successful neural network algorithms applied to the problem of data compression. In this compression algorithm 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. In the hidden layer, 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. Each sub-image may then be used to train an individual ANN. Experiments have been conducted that have successfully compressed and decompressed medical images with impressive compression ratios and little or no loss of data. Experiments have also been conducted to show the performance of a network when trained with a particular image, and then tested with a larger image. It was found that the generalization capability of the back propagation ANN could cope sufficiently when the difficulty of the problem was substantially increased. It starts with a network that contains only a single hidden unit in the hidden layer. The network is trained and if the weights obtained after training do not give a response with a desired accuracy then one more hidden unit is added and the network is again retrained. This process is repeated until a final network with the desired accuracy has been obtained.

Kohonen Self-Organising Neural Network for Image Compression

Another neural-type algorithm that has also been used for medical image compression is the Kohonen network. It was been found that the Kohonen network can give better results for data compression than the BP neural network. The Kohonen network uses an unsupervised training algorithm. There is no feedback in the Kohonen network, and 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 is computed. The weights of the node with the minimum distance, along with its neighbouring 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.

PROPOSED TECHNIQUE FOR MEDICAL IMAGE COMPRESSION

The steps proposed for image compression are as follows:

1. Binarisation,
2. Segmentation of the image,
3. Preparation of training pairs,
4. Exclusion of similar training pairs,
5. Compressing the image using the Direct Solution Method (DSM)
6. Reconstruction of the image.

Binarisation

The image is first converted into a monochrome bitmap. Each pixel of the image is then converted into a “1” or “0”. The black pixels of the image are converted into “1s” and the white pixels are converted to “0s”. Binarisation is very important, for further preprocessing of the image.

Segmentation of Image

The image is then segmented into smaller images or windows. This step is very important so as to limit the number of inputs into the ANN. This step is also important to later exclude redundant training pairs.

Preparation of training pairs

After the larger image is broken down into smaller more usable windows, it is necessary to alter them into a form ready for use with the ANN. A file is prepared where each window is written as two identical vectors to form a training pair. In other words, the first vector would be the input vector and the second vector would be the desired output.

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Exclusion of similar training pairs
As many of the images tested were extremely large, there were many similar training pairs after segmentation. To eliminate this redundant information, a program was used to search the training file for similar training pairs and delete them. This not only reduced the number of redundant training pairs, but reduced training time of the ANN.

Compression Of Image Using Ann And The Direct Solution Method
At this stage the training data was ready for input into the ANN. Instead of using a time consuming iterative method for training the network, the problem was solved by a DSM. The image was "compressed" in the hidden units of the ANN. The weights (unknowns) are determined by solving a system of equations, which may then be used for "decompression" of the image.

Reconstruction of the image

Finally, the output produced by the ANN in the form of decompressed vectors or windows, is reconstructed to produce the full original image. The binarised pixels are converted into their proper graphical representation, and are compared with the original image.

EXPERIMENTAL METHOD

Image Acquisition
The images were scanned using medical imaging system and then saved in Tagged Image Format (TIF). They were then easily moved across PC platforms to an IBM compatible machine running Windows 7. The image was then converted to a solely black and white (monochrome) format. This was necessary for binarisation to be completed in further steps.

Preprocessing
Binarisation is a technique that converts the black and white pixels of the BMP-type image into "1's" and"0's", respectively. In this form, segmentation and other preprocessing techniques can be executed much more easily. Binarisation was performed using an already implemented program written in ANSI C. Segmentation has already been employed to develop a preliminary database of sample images. A simple segmentation program was implemented in C to segment larger images into smaller blocks ready for use in conjunction with a classification method.

Neural Network Algorithm
Neural network algorithm is important to obtain accurate classification rates for the images acquired. A neural network using the Direct Solution Method was chosen due to its ability to train a neural network faster than existing ANN algorithms.

Implementation Platform and Language
The segmentation, preprocessing and classification programs were implemented and run using the SP2 Supercomputer. To evaluate the performance of the proposed approach for image compression neural network algorithm is implemented on MATLAB 2010b on medical images.

Experiments
The data compression experiments were conducted using various images, varying in size. Most of the images were quite large, therefore segmentation is done so that the images

were broken down into smaller windows. Window sizes between 8x8 and 16x16 pixels in dimension were chosen to limit the inputs into the network. The neural network results in improved compression ration which will accomplished by making use of clinically relevant regions as defined by physicians. Images taken of patients will be aligned to prestored image models stored in an atlas. The atlas will contain models of typical classes of images. If we are trying to compress a chest X-ray image, then it will be matched with a prestored chest X-ray model that is stored in the atlas. Once an image is aligned to its corresponding model in the atlas, the two can then be aligned and the clinically relevant regions defined on this atlas image will be used to define the relevant region on the newly scanned patient image. A prestored database of common film types such as X-rays of the head and chest can be stored. These will be used as templates and the collection will serve as the atlas. When an X-ray is taken, the software will be able to determine the gender and age of the patient based on the header information stored in the image. The header will also indicate what body part is being imaged (head, chest, foot, etc…). This information is needed to find the appropriate template in the atlas. Next, the X-ray is aligned via the proposed deformable object model matching mutual information of the image against the prestored template. Now the two images are subtracted. Whatever is left is considered a residual. The residuals are encoded by compression. If the alignment has been done well, the residuals should be minimized which means the compression has been maximized. For reconstruction, the compressed residual medical image is first decompressed. Then the decompressed residual is added back to the template according to the model and the original image should be obtained. This would be beneficial for teleradiology applications since only the compressed residual image needs to be stored along with the atlas. Advantage of this method is that it does not matter as much what the underlying data type is. It can be 2D or it can be 3D. Any compression data rate can be achieved. It is possible to get very high compression rates with good alignment using this techniques. Next it produces 'residuals of residuals' can be examined for possible improvement in storage savings. Consider a person whose X-rays have been taken over time. The first X-ray can be stored after alignment. Then the difference between the second X-ray and the first X-ray after alignment is computed. This is considered the 'residual of residuals'. But there are two problems with this idea. The computing cost increases, and all of the residuals are useless if you lose the starting image. Long-term X-ray differences can also be explored. Another advantage of this method is that the 'residuals of residuals' can be examined for possible improvement in storage savings. Using the clinically relevant region approach, the compressed file size is 519371 bytes. This gives a compression ratio of 3.495:1 or 2.289 bpp. The clinically relevant region area takes up 59.0% of the entire image area. So, even though the clinically relevant region is so large, the compression ratio has still been improved over the 2.358:1 ratio. Also using the clinically relevant region approach on the residual, the compressed file size is 1380229 bytes. This gives a compression ratio of 3.704:1 or 2.160 bpp. The clinically relevant region areas take 1up 42.0% of the entire image area. The compression ratio has improved over 100% over the 11:1 ratio for the lossless compression of the residual image.

A sample image was taken as the input to be compressed. At each instance (1:100, 1:100) pixels were considered. Now using mat2v function the matrix was arranged column wise. The target was made equal to the input and the matrix was scaled down. There are 4 neurons in the first layer (compression) and 16 neurons in the second layer (decompression) on the network. The first layer used tangent sigmoid function and the linear function in the second layer. Then the training was performed using neural network algorithm. The data from an image is encoded into a construction of the hidden and output weight matrices by the training procedure.From the two-layer network the hidden-half of is used to encode images. The image is decoded (reconstructed) using the output-half the two-layer network.

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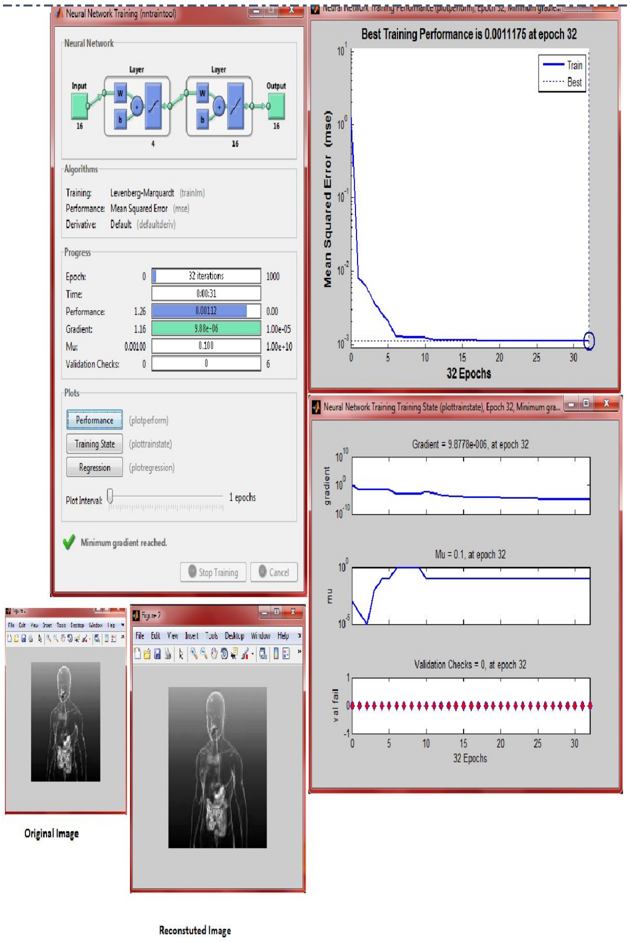

Figure 1 MI -1

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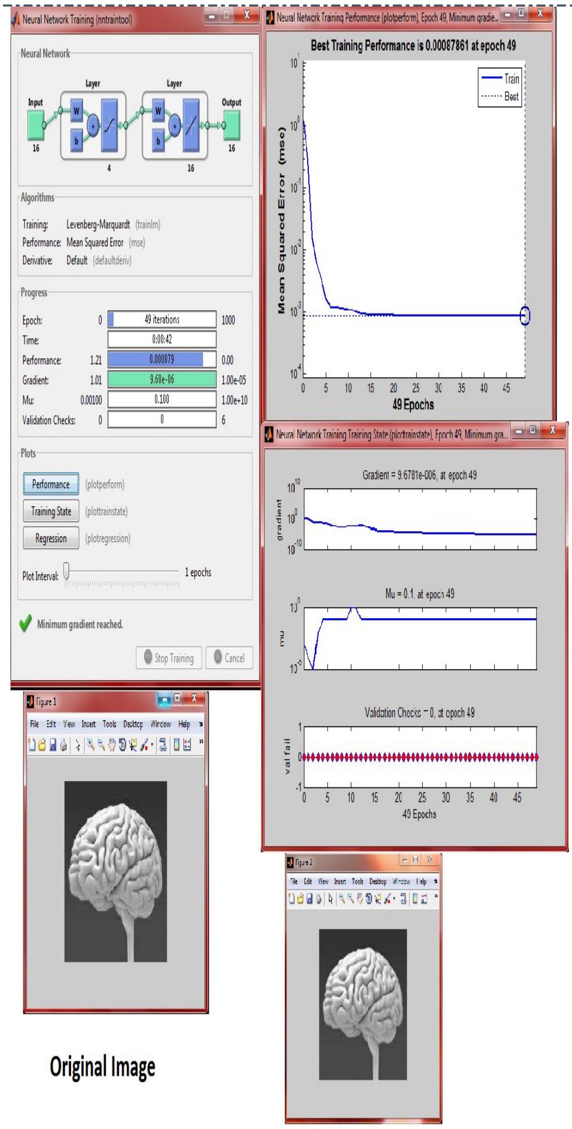

Original Image

Reconstructed Image

Figure 2 MI-2

RESULT

The evaluation of the proposed approach in image compression is performed based on the following factors; PSNR and MSE and compression ratio values. Using this technique we get maximum 50% of compression ratio and there is maximum 5 to 9 dpp of noise is formed. So this technique is useful for image compression to reduce the image size.

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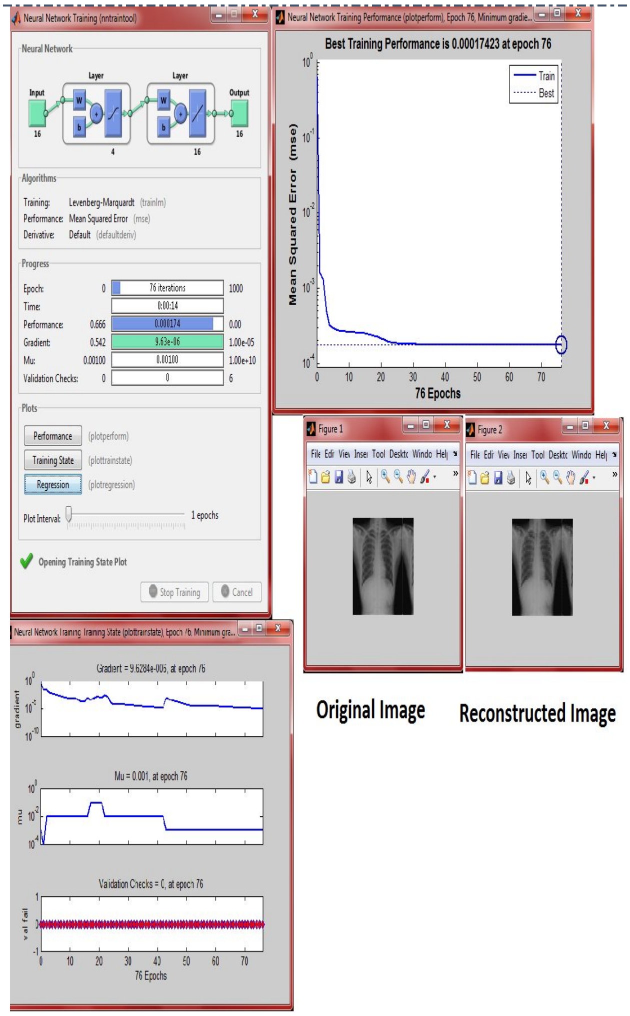

Figure 3 MI-3

No. of Iteration	No. of Block size	PSNR	MSE	Compression Ratio	Time of Execution(sec)
48	100	8.5399	9101	50.25	09
66	108	8.9369	8306	30.90	13
28	224	5.8723	1682	37.5	23
159	224	8.8194	8533	37.5	132

CONCLUSION

It is observed that proposed algorithm has a simple algorithms but it is able to achieve good quality performance. ANN based compression procedure does not require prior knowledge of the image source like JPEG, JPEG2000 does (to optimize, quantization tables). Since ANN also has the desirable properties resulting from its successive approximation quantization, different topologies. The results obtained from Back Propagation neural networks found much better results when compared to conventional JPEG2000 approach. The computing world has a lot to achievement from neural networks. There is no need to develop an algorithm to perform a specific task; i.e. It is not necessary to understand the internal mechanisms of that task. They are also very well suitable for real time systems because their architecture is parallel so that it has fast response and computational times. Neural networks also suitable for areas of research such as neurology and psychology. They are regularly used to model parts of living organisms and to investigate the internal mechanisms of the brain. Perhaps the most exciting aspect of neural networks is the possibility that some day 'conscious' networks might be produced. There are a number of scientists arguing that consciousness is a 'mechanical' property and that 'conscious' neural networks are a realistic possibility. Even though neural networks have a huge possibility we will only use to get the best of them when they are integrated with computing, AI, fuzzy logic and related subjects. Neural networks performance is best for achieving the goal where other methods do not, recognizing and matching complicated, vague, or incomplete patterns

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