A Segmentation based Retrieval of Medical MRI Images in Telemedicine

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Telemedicine facilitates consultation with the health care provider located in a remote location by using telecommunication technology. Information and communication technologies are the backbone in telemedicine to provide clinical services for patients. A vital component in the telemedicine process is the transfer of medical images in order to diagnose a disease. The large size of medical images compounded with bandwidth limitations in rural areas are challenges that need to be addressed. Content based image retrieval techniques are used to retrieve relevant images from the database. It has successfully been implemented for medical image retrieval. This paper investigates the medical image retrieval problem for telemedicine using compressed images for efficient utilization of bandwidth. A novel feature extraction and a genetic optimized neural network classifier were proposed in this study. Experimental studies revealed better classification accuracy for compressed images when compared to the uncompressed ones. Diffusion Weighted Images DWI images of the brain were used to test the efficiency of the proposed classifier to retrieve medical images affected with Stroke disease.

Keywords: Segmentation, Compression, Image Retrieval, Telemedicine and Neural Network.

Introduction

Telemedicine aims on the overall improvement in the medical scenario in terms of better patient care, high quality expert consultation from a remote location and cost effective patient transfers to the site of the doctor thereby diminishing the overall medical expense for a more specialized treatment1. It integrates information and communication technologies to provide expert-based healthcare services exchanging information required for diagnosis, consultation and also for references. It includes diagnostic, remote monitoring and interactive services and also drug evaluation, medical research, training, and teaching. People in remote and isolated regions find telemedicine extremely helpful. Telemedicine is also useful in critical care/emergency situations, but its main challenges are limited bandwidth, large data volume and availability of expert opinion2,3.

In this study, Magnetic Resonance Imaging (MRI) images of the brain were analyzed for identification of patients with Stroke. MRI images show location and extent of brain injury caused by Stroke. A clear distinction between ischemic stroke and hemorrhagic Stroke could be studied from MRI imaging. CBIR provided clinical diagnostic support through classifying and retrieving relevant cases. Lahmiri and Boukadoum proposed a three-stage approach for design which consisted of second-level discrete wavelet transform image decomposition under study, feature extraction from the LH and HL sub-bands using first order statistics, followed by classification by k-nearest neighbor (k-NN), learning vector quantization (LVQ), and probabilistic neural networks (PNN) algorithms. The experimental results showed that using an ensemble classifier improved correct classification rates4. El-Sayed et al5 presented two hybrid techniques for the classification of the magnetic resonance human brain images. The proposed technique consisted of three stages including feature extraction, dimensionality reduction, and classification. The first stage included obtaining features related with MRI images using discrete wavelet transformation (DWT). The next stage had features of magnetic resonance images (MRI) being reduced using principle component analysis (PCA) for the more essential features. In the classification stage, two classifiers based on supervised machine learning were developed. The first classifier was based on feed forward backpropagation artificial neural network (FP- ANN) and the second classifier on k-nearest neighbor (k-NN). The classifiers classified subjects as normal or abnormal MRI human images. A classification with a success rate of 95.6% and 98.6% was obtained by the two proposed classifiers FP-ANN and k-NN respectively.
Ebadian et al. proposed a method to study the ischemic stroke using Artificial Neural Network (ANN). The method identified the extent of ischemic lesion recovery. Experiments using new dataset showed that the prediction made by the ANN had excellent overall performance and was correlated well for the 3-month ischemic lesion on T2-Weighted image. Kabir et al. proposed a multimodal Markov random field model for automatic segmentation of stroke lesions on MR multi-sequences. Gutierrez-Celaya et al. automated the evaluation of stroke chronic patient’s motor functions. The proposed method helped to predict rehabilitation possibilities of patients after stroke. The MLP was trained to discriminate statistical patterns of brain activations using non-correlated independent image parameter vectors. Since no major work has been done for image retrieval of compressed image, this work attempts to bridge the gap by using near lossless techniques for CBIR.

Limited bandwidth and voluminous diagnostic data requiring transmission is a major issue in telemedicine, which have been addressed by image compression. Image compression reduced data required to represent an image and also at the same time reduced storage and transmission requirements. Image redundancies were removed during the compression process to yield a compact representation of the original image. Lossless compression techniques were used when the original image was to be perfectly recovered. Similarly, lossy compression techniques were used when high compression rate was required with minor detail loss. This study also surveyed compressed image retrieval as bandwidth was a major issue. It could be understood from the literature survey that various techniques have been proposed for CBIR and medical image compression for telemedicine applications. However, investigations in the area of Image Retrieval (IR) for near lossless compressed images have not been carried out extensively. This paper investigates feature extraction techniques in the frequency domain by extracting the features using Fast Fourier Transform and proposes a modified Fast Fourier Transform. Investigations are also carried out to find the classification accuracy of the proposed feature extraction technique using an improved neural network.

Materials and Methods

In order to test the effectiveness of our approach, a set of 52 DWI scan images consisting of 25 positive stroke patients. These images were provided by the MRI Department of Vijaya Health Centre, India. The MRI images were reviewed by an expert in the radiology department for a precise classification of patients with positive stroke. Experiments were performed on the uncompressed and the compressed images to show the effectiveness of compressed images for image retrieval.

**Experiment 1 for uncompressed images**
1. Preprocess the image using a median filter for noise removal.
2. Segment the preprocessed image into ROI (Region of Interest) and non ROI.
3. Extract features of the ROI using IRS-FFT.
4. Feature Reduction using Information Gain.
5. Classification using proposed Genetic Optimized parallel neural network for 20, 40, 60, 80 and 100 features.
6. Performance Evaluation of the proposed system with the MLP-Neural Network.

**Experiment 2 for Compressed Images**
1. Preprocess the image using a median filter.
2. Segment the preprocessed image into ROI (Region of Interest) and non ROI.
3. Compression of ROI using Haar wavelet with Huffman encoding.
4. Extract features using IRS-FFT.
5. Feature Reduction using Information Gain.
6. Classification using proposed Genetic Optimized parallel neural network for 20, 40, 60, 80 and 100 attributes.
7. Performance Evaluation of the proposed system with MLP-Neural Network.

**Segmentation**

Edge detection in image processing is typically used for data reduction by identifying the Region of Interest (ROI). The structural properties of the image are preserved and the unwanted background information are filtered out. There are many ways to perform edge detection. In the present study, a 5x5 convolution mask is used, to detect the edges and thereby extract the Region of interest. Fig. 1 shows the flowchart of the segmentation process used in the experimental set up. The highlighted part shows the ROI extracted for some of the DWI brain images used in the present study as depicted in Fig. 2.

The proposed method is subdivided to the following techniques comprising compression, feature extraction and classification. Haar Wavelet for decomposition and
Huffman encoding has been used to compress the images. The Haar Transform (HT) transforms the image from the space domain to a local frequency domain \(14-15\).

**Proposed Feature Extraction**

The proposed feature extraction has been explained in detail by the authors in previous studies \(16\). The most essential features for classification are determined by Information Gain. The information gain value of each feature is computed across all classes and ranked from highest to the lowest. Features with high value of information gain are more informative. The top \(N\) features are selected for classification. In this work, 20, 40, 60, 80 and 100 features were selected, in order to evaluate the classification accuracy.

**Classification by Genetic Optimized Parallel Neural Network**

The authors have investigated various classification techniques including Multi-layer Perceptron Neural Network\(17-18\). Based on the previous studies, an improvement over the MLP Neural Network is proposed namely Genetic Optimized Parallel Multilayer Perceptron Neural Network (GOP-MLP NN). It is an extension of the existing Multi-layer perceptron (MLP) model. Full interconnectivity between the layers is not achieved, unlike in the MLP Neural Network. The network processing the input signals uses several parallel MLP's as it reduces the number of weights required and hence the training time for the network is reduced over traditional MLP network\(19-21\).

The proposed neural network consists of two parallel MLP’s with each performing different sub tasks. The first sub module MLP uses the first 50\% of the attributes and the remaining are used by the second sub module. The number of weights is reduced by 50\% using this process. Each MLP consists of two layers. A Genetic Optimization function is introduced in the second hidden layer of the proposed network to find the best learning rule and momentum. The proposed network was trained using 10 fold cross validation.

The proposed GOP MLP Neural Network employs two hidden layers. The transfer function used by the upper hidden layer is the tanh activation function and the lower hidden layer uses the sigmoid activation function. A step size of 0.1 and a momentum of 0.7 are used. The learning rule of the output layer is the momentum.

The learning capability and the generalization capability of the proposed neural network model is calculated using the performance measure of the mean square error (MSE). The MSE is given by

\[
MSE = \frac{\sum_{j=0}^{E} \sum_{i=0}^{N} (o_{ij} - y_{ij})^2}{EN} \quad \ldots(1)
\]

where,
- \(E\) is the number of processing elements
- \(N\) is the number of exemplars
- \(o\) is the desired output for exemplar \(i\) at processing element \(j\)
- \(y\) is the obtained output for exemplar \(i\) at processing element \(j\)

The tanh will squash the range of each neuron to between -1 and 1. The tanh activation function is given by

\[
tanh(i) = \frac{e^i - e^{-i}}{e^i + e^{-i}} \quad \ldots(2)
\]

where, \(i\) is the sum of the input patterns.

The GOP uses Genetic optimization in the hidden layer of the network. Genetic Algorithms (GA) are a class of optimization algorithms inspired by evolution\(22-28\). The steps in GA include reproduction, cross over and mutation to evolve better solutions. Generally the solutions available are evaluated using fitness function. Based on
the fitness function, the evolutionary process is iterated
till an ideal solution is reached or a specific number
generations have occurred. The proposed NN
architecture is optimized for ideal momentum value using
GA with the following parameters.
A population size of 10 with a maximum of 20
generations was used. The lower and upper bound
momentum optimization value are 0.05 and 0.95
respectively. A one point crossover operation with
Roulette wheel encoding mechanism with a crossover
probability of 0.75 was used. A uniform mutation
probability of 0.02 was used with 500 iterations.

Experimental Results and Discussions
From Table 1, it could be observed that, even with a
very low number of features, the proposed feature
extraction classifier is able to classify stroke and non-
stroke images with good results. The classification
accuracy of the proposed methods has improved by 6.4%
when 40 features were selected. This becomes relevant
as the proposed system also provides good precision
which becomes a desirable feature for retrieval of similar
images for diagnosis. The classification accuracy,
precision and recall are computed as

$$\text{Classification Accuracy} = \frac{\text{Number of correctly classified samples}}{\text{Total Number of Tested Samples}} \times 100$$

... (3)

Precision is the total number of relevant images
retrieved to the total number of images retrieved. Recall
is the total number of relevant images retrieved to the
total number of images in the database. Slightly lower
values of recall does not affect the proposed system as
the data under consideration is stroke and non-stroke images and this forms one of the major outputs for brain MRI shown in Fig 3.

**Compression Achieved**

The ROI mask is used to segment the image into Region of Interest and Non Region of Interest. The ROI is compressed using Haar wavelet with a decomposition value of 1. The non ROI part of the image uses a higher level of decomposition, up to 5 levels. The following parameters are determined to evaluate the efficiency of compression of the techniques.

\[
\text{Compression ratio} = \frac{\text{Original file size} - \text{Compressed file size}}{\text{Original file size}} \times 100 \quad \text{...(4)}
\]

\[
\text{Compression Factor} = \frac{100}{\text{Compression ratio}} \quad \text{...(5)}
\]

Two of the error metrics used to compare the various image compression techniques are Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR). The MSE is the cumulative squared error between the compressed and the original image, whereas PSNR is a measure of the peak error. A lower value for MSE means lesser error, and as seen from the inverse relation between the MSE and PSNR, this translates to a high

<table>
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<th>No. of features</th>
<th>Parameters</th>
<th>Classifiers</th>
<th>Feature Extraction using FFT</th>
<th>Feature Extraction using proposed IRS FFT</th>
<th>Feature Extraction using FFT</th>
<th>Feature Extraction using proposed IRS FFT</th>
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<td>20</td>
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<tr>
<td>Recall</td>
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<td>0.89</td>
<td>1</td>
<td>0.86</td>
</tr>
<tr>
<td>Classification</td>
<td></td>
<td>MLP</td>
<td>90.38</td>
<td>94.23</td>
<td>92.31</td>
<td>94.23</td>
</tr>
<tr>
<td>Accuracy</td>
<td></td>
<td>GOPNN</td>
<td>94.23</td>
<td>96.15</td>
<td>94.23</td>
<td>98.08</td>
</tr>
</tbody>
</table>

| 40              |            | MLP         | 0.96                         | 0.96                                     | 1                            | 1                                        |
| Precision       |            | GOPNN       | 1                            | 1                                        | 1                            | 1                                        |
| Recall          |            | MLP         | 0.86                         | 0.92                                     | 0.86                         | 0.89                                     |
| Classification  |            | GOPNN       | 0.89                         | 0.93                                     | 0.89                         | 0.96                                     |
| Accuracy        |            | MLP         | 88.46                        | 94.23                                    | 92.31                        | 94.23                                    |

| 60              |            | MLP         | 92.31                        | 94.23                                    | 92.31                        | 98.08                                    |
| Precision       |            | GOPNN       | 94.23                        | 96.15                                    | 94.23                        | 98.08                                    |
| Recall          |            | MLP         | 0.92                         | 0.96                                     | 1                            | 1                                        |
| Classification  |            | GOPNN       | 1                            | 1                                        | 1                            | 1                                        |
| Accuracy        |            | MLP         | 90.38                        | 94.23                                    | 92.31                        | 94.23                                    |

| 80              |            | MLP         | 0.96                         | 0.96                                     | 1                            | 1                                        |
| Precision       |            | GOPNN       | 1                            | 1                                        | 1                            | 1                                        |
| Recall          |            | MLP         | 0.86                         | 0.92                                     | 0.86                         | 0.89                                     |
| Classification  |            | GOPNN       | 0.89                         | 0.93                                     | 0.96                         | 0.96                                     |
| Accuracy        |            | MLP         | 90.38                        | 94.23                                    | 92.31                        | 94.23                                    |

| 100             |            | MLP         | 94.23                        | 96.15                                    | 98.08                        | 98.08                                    |
| Precision       |            | GOPNN       | 94.23                        | 96.15                                    | 98.08                        | 98.08                                    |
| Recall          |            | MLP         | 0.96                         | 0.96                                     | 1                            | 1                                        |
| Classification  |            | GOPNN       | 0.86                         | 0.92                                     | 0.86                         | 0.89                                     |
| Accuracy        |            | MLP         | 90.38                        | 94.23                                    | 92.31                        | 94.23                                    |

Table 1—Experimental results for proposed system
value of PSNR. Logically, a higher value of PSNR is good because it means that the ratio of Signal to Noise is higher. Here, the ‘signal’ is the original image, and the ‘noise’ is the error in reconstruction. The compression parameters namely the number of bits per pixel BPP, Mean Square Error MSE, Compression ratio CR and the Peak Signal to noise ratio PSNR were determined for the MRI brain images. The compression ratio is far better on maintaining PSNR value greater than 40. The average compression factor achieved by the ROI is 2.691 and 4.195 for non ROI areas.

Conclusion

In this paper, the medical images are compressed based on ROI and non ROI to achieve better compression ratio for the image. A novel feature extraction technique improvising on the Fast Fourier Transform (FFT) was proposed. A novel neural network with genetic optimization to find the ideal momentum was proposed. Experiments were conducted using the proposed feature extraction method and novel classifier for uncompressed and compressed images. A two class problem on MRI stroke images was used. The extracted features were reduced using Information Gain (IG) and classified using Multi-Layer Perceptron Neural Network and proposed NN architecture with genetic optimization. Results show the improvement in precision using the proposed system. The work also showed that medical image compression with retained PSNR value of 40 and above can be effectively used for classification without reduction in classification accuracy. Over 35% savings in bandwidth is observed due to compression which is relevant for telemedicine. Further work needs to be done to compare the efficacy of the proposed method with multi class problem.

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References


