A Medical Image Retrieval Framework using Genetically Optimized Elman Neural Network

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Abstract: In this paper, a Content Based Image Retrieval (CBIR) framework for medical images has been presented. An algorithm based on energy information obtained from Hilbert Transform for extracting features from medical images based on imaging modalities. The features are selected on the basis of the correlation among the extracted vectors depending upon the class label. An enhanced Genetic Algorithm Optimized based Elman (GAOE) Neural Network for image retrieval is presented. The performance of proposed method has been evaluated using a dataset consisting of 180 medical images. The experimental results demonstrated that the efficiency of the GAOE neural network is high compared to methods using low-level features.

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1. Introduction

The development of health care systems has been the area of interest for many researchers in the recent years. The use of digital medical images in the form of X-rays, MRI, CT and Ultrasound, has revolutionized the diagnosis and clinical pathology. With the advent of database technologies, huge medical images database are created for various applications. The management of the large image database poses challenges for indexing and classifying the images for efficient use. This challenge has motivated the researchers to develop various image retrieval algorithms in the past two decades. Content Based Image Retrieval (CBIR) technique has been used to retrieve the images using query parameter [1, 2]. Based on the query image, similar images can be retrieved from the database. CBIR finds wide-ranging applications in the medical field as medical professionals use it for diagnosis and planning treatment.

Image retrieval plays a vital role in managing large amount of visual information in medical applications [3]. The performance of the image retrieval system depends upon the multi-dimensional feature vector formed by information extracted from images. The similarity measures are computed and images similar to query images in the database are identified, which have the lowest distance metrics with respect to the query image. The transform methods are widely used in the image processing [4, 5,]. In transform method, a large number of coefficients can be ignored to reduce the size of the feature vector. Park, et al., [6] proposed a model for automatic retrieval of object models. The feature extraction module extracts object region by segmentation and performs a one-level wavelet transform to normalize the image. The Shape and texture information is acquired from the normalized image. The feature model also extracts a structural feature value with diagonal moment which gives the best retrieval rate.

Sadek, et al., [7] developed a new architecture for CBIR using Splines Neural Network based image retrieval (SNNIR). The splines neural network facilitates the proposed system to determine nonlinear relationship between different features in images which betters the comparison accuracy. A method, PANDA, for formalizing patterns of next generation database systems for pattern representation and management was developed by Iakovidis, et al., [8]. The low level features extracted from the medical images were clustered in the feature space forming higher level, semantically meaningful patterns. The Expectation-maximization algorithm was used for automatic determination of the number of clusters. The similarity between the clusters was estimated as a function of the similarity of both their structures and the measure of components. Ahmed kharat, et al., [9] proposed a spatial gray level dependence method to extract features from medical images. For retrieval of images, Genetic Algorithm (GA) and Support vector machine (SVM) was used. A Gaussian fuzzy feed forward neural network and Genetic algorithm (GA) for retrieval and optimization of medical images was developed by Durai, et al., [10].

Neural networks are successfully applied in medical image processing and various models for retrieval have been reported in the literature [11, 12]. The popularity of neural network is due to its ability to handle issues faced by the traditional image-processing algorithms. The artificial neural network algorithms developed for medical image processing are more intelligent than the conventional techniques [13]. The neural network performance depends upon the learning rate and momentum. To find optimal values of learning rate and momentum, optimization procedures are incorporated. Genetic algorithms are used for optimization and are used to find global optimum values.

This paper proposes an improved image retrieval system based on the feature vectors extracted from the image using Hilbert Transform (HT) and select the relevant features for retrieval based on the correlation among the attributes. A novel retrieval algorithm Genetic Algorithm Optimized Elman (GAOE) Neural network is proposed by modifying the existing Elman Network by introducing optimization for the learning rate and momentum in the hidden layer.

2. Methodology

The proposed CBIR system classifies images using the following procedure. Medical images available in the public domain are obtained for investigating the proposed work. The flow chart of the proposed CBIR system is shown in Figure 2. Following are the step of the proposed CBIR system.

Step 1: Image acquisition

Sets of the images are labelled according to the class.

Step 2: Filtering and segmentation is applied to images for noise removal [14].

The median is calculated by first sorting all the pixel values from the surrounding neighbourhood into numerical order. The pixels are then replaced considering the middle pixel value. Median filtering is normally used to reduce noise in an image. Noise appears in an image as bright spots (or spikes).

9	7	7
5	180	9
6	12	16

Figure 1. Median values

In the 3×3 square neighbourhood shown in Fig. 1, all the gray levels in the set are between 5 and 20, except for the centre value as 180 which is later replaced by the median value to eliminate the distractive effect from the image.

Step 3: Feature extraction

a. The Hilbert transform coefficients are extracted [15]
b. Extract significant coefficients by ranking the coefficients with respect to the class label
c. Select top 50 coefficients for training the proposed neural network classifier
d. Store the feature vector in transactional database

Step 4: Image retrieval algorithm training

a. Train proposed neural network using training data
b. Test proposed algorithm with test data without providing class label
c. Compare actual class with predicted class output
   i. Measure retrieval accuracy
   ii. Measure precision
   iii. Measure recall

Step 5: Optimize the learning rate and momentum using Genetic algorithm measure retrieval accuracy, precision and recall

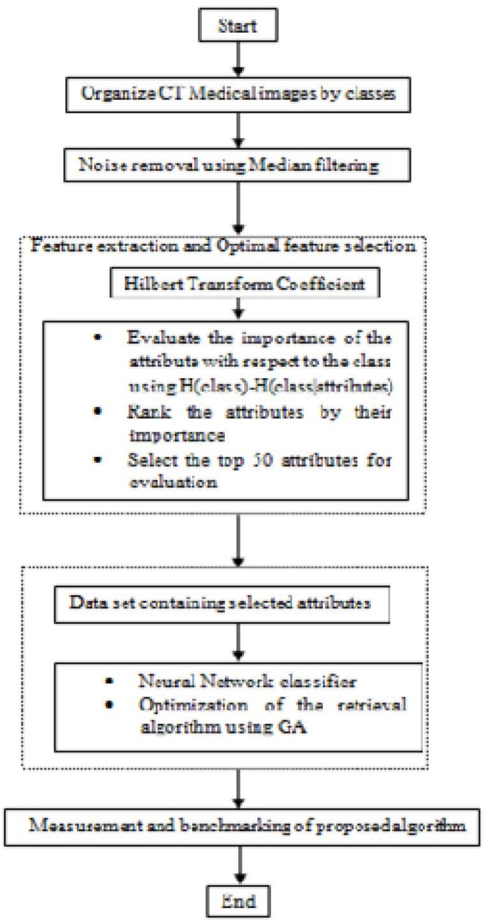


Figure 2. Flow chart of the proposed CBIR system

2.1 Neural Networks For Medical Image Retrieval

Neural networks are built on the principles of neuron; the simple mathematical representation of the neuron is the perceptron. The feed-forward neural network is a network of perceptrons which are connected by links and is characterized by weights. Mathematically a neuron is given by:

where $x_1,...,x_n$ are the input signals, $w_1,...,w_n$ are weights of the neuron, φ is the activation function, b is the bias and y is the output signal.

Output from neural network is denoted as closed unit interval with values of either [0, 1] or [-1, 1]. The feed forward neural network consists of an input layer, one or more hidden layer and an output layer. Recurrent Neural Networks (RNN) is a special type of neural network used to generate temporal outputs of nonlinear systems [16] and can simulate any time series. Elman networks are commonly used RNN. Fig 3 shows a general architecture of Elman network with one hidden layer [17].

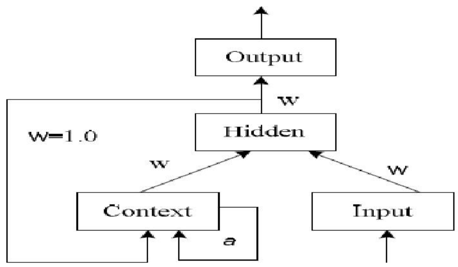


Figure 3. The basic architecture of Elman Network

After the calculation of hidden units, their values are computed to get network output and are stored as extra inputs for use for the network's next operation. Hence, recurrent contexts provide a weighted sum of earlier values of hidden units as input to hidden units. As seen in Figure 4, activations are copied from the hidden layer to context layer on a one-for-one basis, with fixed weight of 1.0 (w=1.0). The forward connection weight is then trained between hidden units and context units and other weights. When self-connections are introduced to context unit, values of self-connections weights (a) are between 0.0 and 1.0 (usually 0.5) before training starts, thus, improving the performance of the ENN. With weights (a) at 0, the network is original ENN [18].

Figure 4 illustrates the internal learning process of ENNs through an error back-propagation algorithm. The training this network is not easy as network output is based on inputs and earlier network inputs. Hence, it has to trace earlier values according to recurrent connections.

Thus, calculation of functional derivatives is not easy, and leads to reduced efficiency with varied signal problems. The learning commonly used in ENN is back propagation algorithm as it adjusts network parameters (weights and thresholds) to reduce error measure function through the use of a gradient descent technique. Hence, it needs computation of error measure differentials, activation function and related analog multiplications.

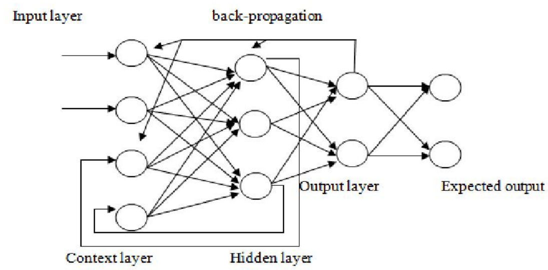


Figure 4. Internal Process Analysis of ENN

2.2. Genetic Algorithms

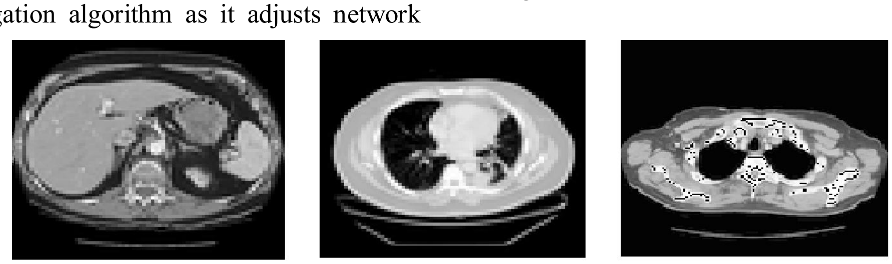
Optimal designing of ENN is done through the use of Genetic Algorithms (GA). Optimization problems are efficiently solved by GAs and also, multiple optima of a specific function is determined. A GA requires three processes to evolve towards optimum solution [19]:

- Selection
- Crossover
- Mutation

Chromosomes codify a point in the search space, and a number of chromosomes form the population. Typical algorithms usually select two parents from the population, mingling their genes to ensure a new result or child, which will enter the population based on the fitness being good. The goodness of the new chromosome is evaluated using fitness functions. The most important aspect would be to get the genetics right for the problem at hand.

3. Results and Discussion

For the experiment, 180 images with three different classes were used. The medical images obtained from scanning portions of the abdomen, chest and brain have been used in the present investigation. The relevant features are selected using correlation among the attributes. Sample medical images used in the experimental setup are shown in Figure 5.



(a) (b) (c)

Figure 5: Images used in the investigation.(a) Brain (b) Abdomen (c) Chest

Noise is present in some of the images used in this investigation. Applying Hilbert transform gives a markedly improved result compared with straightforward directional integration. The Hilbert transform produces a clear contrast between the features and the background as shown in Figure 6

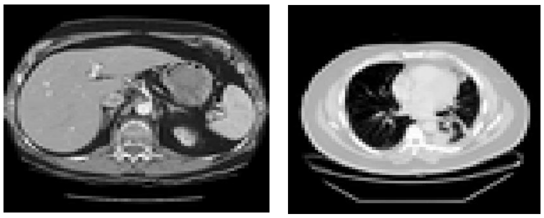


Figure 6. Medical images used in our experiment
(a) Original brain image (b) Transformed image

The pixel values along with Hilbert transform coefficient for a 12x12 window of the image in Fig 7 and is tabulated in Table 1 and Table 2.

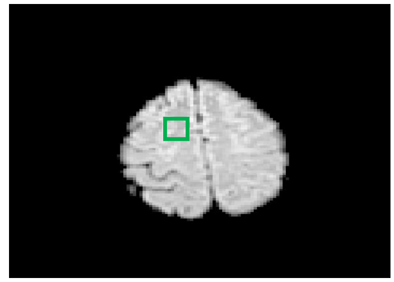


Figure 7. Input Image area whose computed values are shown in Table 1 and 2

Table 1 : A 12x12 window of the pixel values of the input image.

Pixel value

186	55	215	56	110	118	51	78	189	119	57	181
146	164	159	115	80	217	143	120	217	100	101	119
77	52	185	137	131	98	199	129	173	73	138	61
87	58	124	118	104	168	162	66	105	76	160	92
200	136	121	160	212	162	78	148	147	119	116	72
50	62	189	155	206	139	110	85	64	61	188	94
131	188	60	96	54	167	126	112	204	150	171	122
74	188	68	121	174	162	217	147	199	127	215	137
216	171	75	48	92	76	72	89	188	167	138	125
170	71	113	217	119	67	195	96	91	167	102	198
133	160	190	74	141	220	158	153	149	157	63	136
127	136	186	64	210	75	111	91	49	51	152	210

Pixel values

From Table 1, it is observed that the region of interest selected has features which are mean values of the 8 bit spectrum with sharp edges. Hilbert transform are useful for handling the analytical functions. Image signals are changed to be of low-pass instead of band-pass by the Hilbert transform. A ±90°phase shift in both sides of the spectrum is obtained by the contribution of the Fourier spectrum of images to the Hilbert transform. Two dimensional Hilbert transform are utilized in digitized and off-line imaging applications.

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Table 2 : Hilbert coefficients for the selected window with size 12×12 Hilbert coefficients

50.4659	28.1791	26.5079	20.4566	51.2189	60.5417	26.1736	18.6194	16.5942	28.4262	53.9396	60.4527
74.7847	-0.3195	61.6402	71.7242	53.6053	28.6166	11.0603	10.0407	12.5544	13.3998	55.5076	-0.1562
20.2937	53.3252	37.8231	22.4487	50.3198	-0.3127	73.427	10.337	54.9162	46.543	35.6152	63.4471
53.3853	2.5104	4.718	60.178	73.8332	33.6281	51.0619	6.8329	9.1303	-0.923	3.4879	59.3859
23.9689	7.765	15.3665	16.3383	17.8791	-0.9866	38.4392	32.7481	41.9307	5.3785	7.1452	30.6821
53.0574	31.3946	56.8536	23.8499	55.9054	5.3017	50.5881	36.0763	42.3062	59.3749	34.2475	18.4174
4.8307	71.6153	-0.9849	8.9246	19.9535	21.4895	43.3984	29.802	-0.4466	20.4517	22.5406	62.0709
7.1675	2.0875	13.6068	45.7919	-0.0741	48.623	51.1957	60.0264	38.8489	35.6226	6.9761	74.1471
21.3641	37.1461	27.9255	53.9356	48.1551	46.2509	43.3353	49.7201	31.9027	54.2725	64.4508	26.895
9.027	34.2505	48.1616	43.5411	36.2105	43.0962	56.7995	60.6705	53.0288	29.3013	34.674	53.0161
52.7553	37.0296	16.5726	34.3554	-0.8631	68.1155	-0.7096	72.8969	58.3356	57.9618	69.4706	35.337
66.1738	60.5321	58.1204	50.9777	52.3078	22.1232	7.5216	75.9283	41.524	31.9978	31.7299	65.346

The alternative Hilbert transform coefficient to train the retrieval algorithm. The obtained feature attributes using information gain for the given window is shown in Ttable 3.

Table 3 : Extracted features for the 12x12 window.

28.1791	51.2189	26.1736	18.6194	53.9396	60.4527
-0.3195	53.6053	11.0603	10.0407	55.5076	-0.1562
53.3252	50.3198	73.427	10.337	35.6152	63.4471
2.5104	73.8332	51.0619	6.8329	3.4879	59.3859
7.765	17.8791	38.4392	32.7481	7.1452	30.6821
31.3946	55.9054	50.5881	36.0763	34.2475	18.4174

Extracted feature value

The surface plot of the pixel values, the coefficients and the selected attributes are shown in Figure 8 and Figure 9. From Figure 8 it is seen that the energy coefficients have peak values which are distinct among the different classes of images and is critical for the learning algorithm

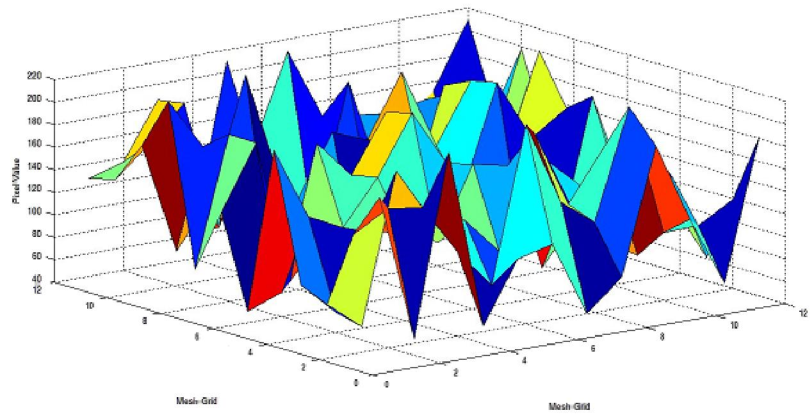

Figure 8. Surface plot of the pixel value for the selected window.

The distinctness of the selected feature is unique for each class of image as shown in Fig 9. It can be seen that distinct features are produced which can be used to train a retrieval algorithm.

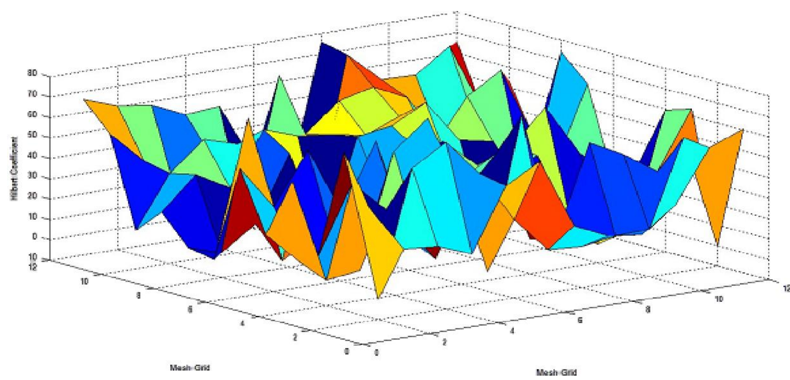

Figure 9. Surface plot of the Energy coefficient in the selected window.

Genetic Algorithm based optimization is introduced in the hidden layer of the Elman network, and the Parameters used in the Proposed Elman Neural Network Model is shown in Table 4.

Table 4: Parameters used in the Proposed Elman Neural Network Model

Parameters	values
Input Neuron	56
Output Neuron	3
Context Unit Time	0.8
Number of Hidden Layer	1
Number of Neurons in hidden layer	4
Transfer function of hidden layer	GA – Tanh
Number of iterations	500

The retrieval accuracy obtained from the proposed algorithm is benchmarked with other algorithms found in the literature. Table 5 lists the retrieval accuracy and Figure 10 shows the same.

Table 5: Retrieval Accuracy

Technique Used	Retrieval Accuracy %
MLP- NN	86.11
Elman NN	88.33
Proposed Elman NN	88.89
Proposed Elman NN with GA	92.22

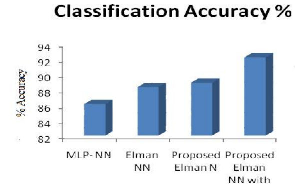

Figure 10. Retrieval Accuracy

Table 6: Precision and Recall of various techniques

Technique Used	Precision	Recall
MLP- NN	0.86	0.86
Elman NN	0.88	0.88
Proposed Elman NN	0.89	0.89
Proposed Elman NN with GA	0.92	0.92

Table 6 shows the precision and recall of various systems. The proposed system also provides good precision which becomes a desirable feature for retrieval of similar images for diagnosis. The precision and recall is computed as

$$\text{Precision} = \frac{\text{Number of relevant images retrived}}{\text{Total number of images retrieved}}$$

$$\text{Recall} = \frac{\text{Number of relevant images retrived}}{\text{Total number of relevant images in the Database}}$$

Equal values of precision and recall indicate the efficacy of the proposed classifier.

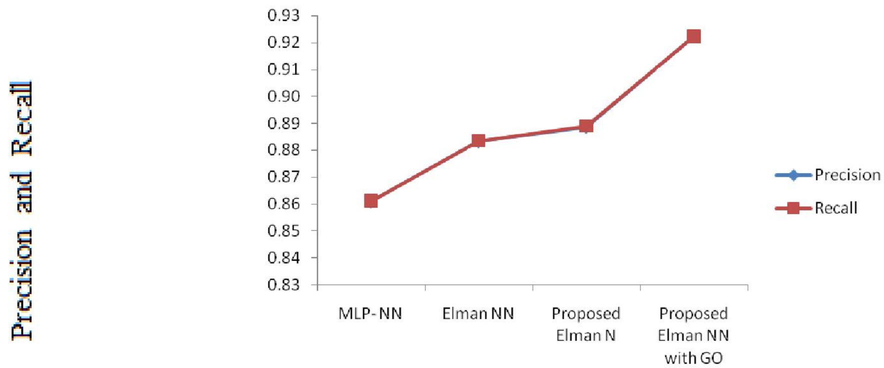

Figure 11. Precision and Recall values for various algorithms

The mean squared error for different learning rate and momentum is shown in figure 12. It can be seen that the network converges fast for a learning rate of 0.1 and momentum of 0.7 indicating that the algorithm converges fast without reaching a local minima.

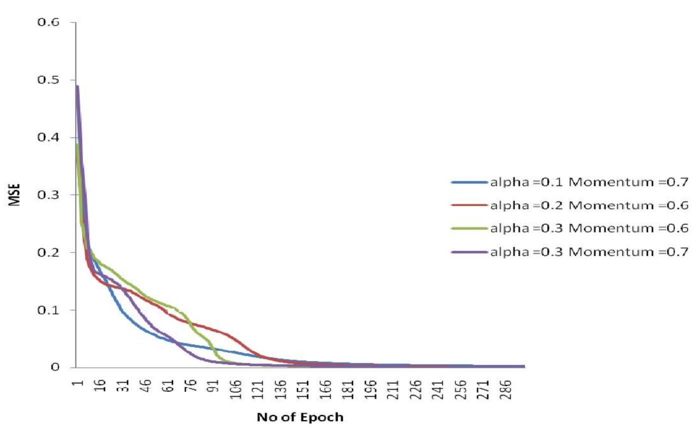

Figure 12. Mean Squared Error for different learning rate and Momentum

4. Conclusion

A novel Genetic Algorithm based Optimized Elman (GAOE) Neural Network for image retrieval is presented. Features were extracted using the fast Hilbert transform and significant features were extracted using Information Gain (IG). The developed retrieval algorithm has been tested on a dataset consisting of 180 medical images and the results demonstrated that the accuracy of 92% is achieved.

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