Baladhandapani ARUNADEVI, Subramaniam Nachimuthu DEEPA

Dept. of EEE, Anna University, Regional Office - Coimbatore

Texture Analysis for 3D Classification of Brain Tumor Tissues

Abstract. *This paper investigates on extending and comparing the Gray level co-occurrence matrices (GLCM) and 3D Gabor filters in volumetric texture analysis of brain tumor tissue classification. The extracted features are sub-selected by genetic algorithm for dimensionality reduction and fed into Extreme Learning Machine Classifier. The organizational prototype of image voxels distinctive to the underlying substrates in a tissue is been evaluated and validated on public and clinical dataset revealing 3D GLCM more appropriate towards brain tumor tissue classification .*

Streszczenie. *W artykule zbadano i porównano algorytmy klasyfikacji tkanki guza mózgu – GLCM i filtry Gabora 3D. Właściwości ekstrakcji były selekcjonowane przy użyciu algorytmu genetycznego i klasyfikatora ELM. (**Analiza tekstury w trzywymiarowej klasyfikacji tkanki guza mózgu**)*

Keywords: 3D MRI – Brain Tumor Tissue – Volumetric Gray Level Co-occurrence matrices – 3D Gabor Filters- Extreme Learning Machine
Słowa kluczowe: guz mózu, klasyfikacja, ekstrakcja, algorytm ELM.

Introduction

Numerous studies on automated brain tumor image classification on three dimensional (3D) models is been developed with little knowledge on workforce of pathologists, with the similar knowledge of interpreting data and giving out accurate results. Since decades, many statistical and machine learning perceptions have been identified for medical image classification. The major deployment of ANN is due to independency in the underlying process from any functional form, even when no prior assumptions can be made and when only data is available.The realization is from the universal approximation property enabling to approximate any continuous function to a desired level of accuracy. Yet, these networks are been considered as 'black box' models and consequently very difficult to interpret in their trained state as studied in [21].

Amongst the various learning algorithms[20,24],the support vector machine is one of the most important and widely used algorithms in medical image classification[2,6]. Several studies have reported that use of support vector machines, in case of both binary and multi SVM,shows better performance, than traditional neural compensating high computational complexity and more time to select . In this state-of-art, Extreme Learning Machine (ELM) [13] is a competitively good solution for such complex tasks. The Extreme learning Machine (ELM),a recent second generation neural network algorithm, is identified as to achieve high quality performance in multifaceted problems and reduced computation time compared with other machine learning algorithms [14]. ELM based model [13,19,25] provides a very fast learning phase for relatively large data sets , that does not require iterative tuning which is dominant in other neural networks.

Michael [16] suggested a model based on elastic atlas warping for brain extraction and statistical pattern recognition for brain interior structures,augmented by a distance from the boundary feature to account for overlapping probability density functions.Cobzas [7] proposed a variational MRI tumor segmentation method that incorporates both atlas-based priors and learned statistical models for tumor and healthy tissue using high multi scale feature set, tested on data from nine patients. Georgiadis put forth a model to evaluate the efficiency of three dimensional(3D) textural features using a pattern recognition system in the task of discriminating primary from metastatic brain tissues on T1 post-contrast MRI series on 67 brain data set [12]. Chris customized a training set using a 'pruning' strategy, for brain tissue classification from 3D MRI using minimum spanning tree graph-theoretic approach to reduce the fraction of incorrectly labelled samples using kNN classifier [3].

This paper will focus on three segments of classification model for tumour on 3D MR brain images;Initially the image processing method, focusing on segmentation and feature extraction model; and secondly on feature sub-selection for in terms of spectral and intensity characteristics using Genetic Algorithm; and last on ELM used to build a robust classifier model for healthy and tumour images. The final section discusses the performance of the proposed approach over existing techniques and conclusions based on this study. The schematic diagram for classification framework is shown in Fig .1.

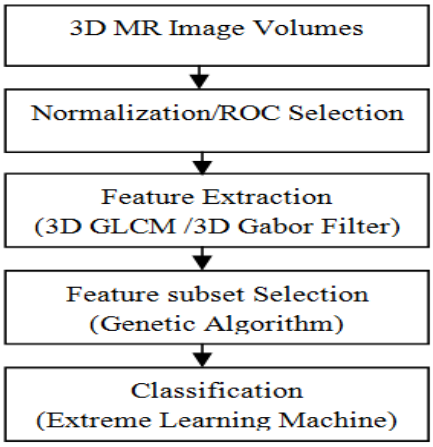

Fig.1. Framework of proposed architecture

Methodology

Texture analysis on images are intrinsic and complex visual patterns that reproduce the data of gray level statistics, anatomical intensity variations, texture, spatial relationships, shape, structure and so on[18]. Image texture analysis aims to interpret and understand these real-world visual patterns, which involves the study of methods broadly used in image filtering, normalization, classification, segmentation, labelling, synthesis and shape from texture. Texture classification involves extracting features from different texture images to build a classifier. It determines to which of a finite number of physically defined classes (such as normal and abnormal tissue) a homogeneous texture region belongs.The development of feature descriptors include region covariance matrix , edgelet , gray level co-occurrence matrix, gradient location and orientation histogram, local binary patterns, HMAX and so on. Numerous other works contrast to different characteristics analysis on textures modelling wavelets and filters[4,11,23].

Proposed Feature Extraction model

Feature extraction transforms the input data into a set of features. In this study, the heterogeneous regions of brain tumors are featured by extending the 2D GLCM to volumetric analysis and 3D Gabor Filter bank . A bank of rich feature set is characterized to aggregate in requisites of intensity, texture, shape, and location [4] . All these features were chosen in analysis with expert radiologists. Image is represented by a function *f(x,y,z) f* three space variables *x, y* and *z*, where *x=0,1,.....N-1 , y=0,1,…M-1* and *z=0,1,…L-1*.The function *f(x,y,z)* can take any value *i=0,1,…G-1* where *G* is total number of intensity levels in the image. The optimal feature set are categorized as :

- Image Intensity (Eg : Mean ,Standard Deviation)
- Texture Features (Eg : Gray level Co-occurrence)
- Spectral Features (Eg : Gabor Filters)

3D Gray Level Co-occurrence Matrix (GLCM)

According to the number of intensity points (pixels) in each combination, Gray Level Co-occurrence Matrix (GLCM) method is a way of extracting second order statistical texture features. 3D co-occurrence matrices are calculated by summing pixel triplet probabilities in a 2D image towards evaluation of capturing spatial dependence of gray-level values across multiple slices are evaluated. The GLCM co-occurrence *P[i ,j]* counts the number of pixel pairs having the intensities *i* and *j*. This matrix is defined by specifying a displacement *d=(dx, dy, dz)* (3x3x3-1=26 neighbours in spatial directions in a 3D space [5 ,9, 22]. For a given feature vector , spatial distances of displacement 1, 2 ,4, and 8 voxels and thirteen directions are selected, resulting in 52(=4*13) displacement vectors (co-occurrence matrices) and 208 scalars (4 (measures) * 52 matrices) = 208). From these co-occurrence matrices, four Haralick texture features [15] (energy, entropy, contrast and homogeneity) are calculated in order to quantify the spatial dependence of gray-level values.Figure 2 represents the 3D GLCM directions .

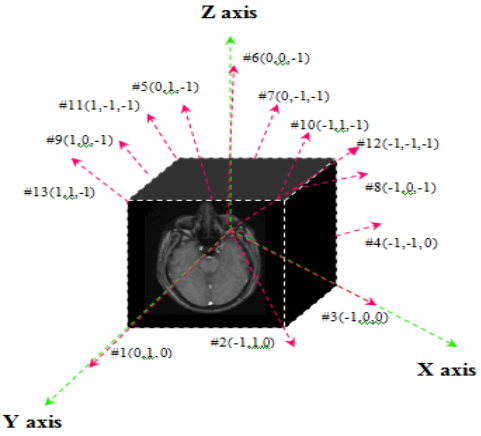

Fig.2. GLCM direction for volumetric data [1]

3D Gabor Filters

The Gabor filters represent an influential spectral feature analysis due to its spatial localization, frequency and orientation selectivity which relates to the human visual system and texture interpretation. The MRI image is filtered by several (complex) Gabor filters and a feature vector is constructed with the absolute values of the responses as components [5, 9] Given the volumetric texture of an image as *a(x,y,z)*, then 3D Gabor filter bank is defined as :

$$h(x,y,z) = a(x,y,z) * b(x,y,z,F_i,\phi_i,\theta_i) \quad (1)$$

$$b(x,y,z,F,\varphi,\theta) = b'.\exp[j2\pi(F\sin\theta\cos\varphi x.F\sin\theta\cos\varphi y.F\cos\theta z) \quad (2)$$

where b' is a 3D Gaussian envelope. Together with radial centre frequency *F* and orientation parameters (ϕ *and* θ) determine a Gabor filter in three dimensions. A set of 3D Gabor filters are generated by choosing different F, ϕ and θ. The implementation includes four centre frequencies for Gabor filters as 0.3536, 0.1768, 0.0884, 0.0442, and frequency bandwidth is one octave. The 6 orientations ϕ and threshold θ are 0, 30, 45, 60, 90 and135 degrees. Thus (4*6*6)144 Gabor filters are used in the experiments. The mean μ and standard deviation σ of Gabor transform coefficients are then extracted as a representation of texture features from 144 Gabor transforms respectively. So a feature vector includes 288 components (=4 (scales) * 36 (orientations) * 2 (measures)) [5,9].

Feature sub-selection model

More textural characteristics imply higher information and potential increase in accuracy.But the paradox is unfortuantely more features tends harder to train the classifier, with the curse of dimensionality .Feature selection finds a subset of original attributes.Using the wrapper approach , a new reduced set of attributes or variables are created by mapping the multi-dimensional space with random subset evaluation into a fewer dimensions.Less discriminatory features are eliminated, leaving a subset of the original features which retains sufficient information to discriminate well among classes , maximising the predicted classification accuracy.

Genetic Algorithm is implemented as a tool to search through the space of possible feature sets [1]. An attribute mask is defined for each state where crossover and mutation are performed. Thus genetic algorithm is explored in the huge space of all possible features subsets , even though the evaluation of the fitness function tends to be expensive.The population of solutions shows convergence behaviour ,with repeated process of selection, one-point crossover and mutation (probability 0.02) within 30 generations in most cases. The GA approach implementation resulted in reduction of 10 strings in population [8].

Extreme Learning Machine (ELM) Classifier

A simple and efficient single-hidden layer feed forward neural network (SLFNN) , the Extreme Learning Machine (ELM)[13] randomly selects input weights and hidden neuron biases without training. The outputs weights are analytically determined using the norm least-square solution and Moore-Penrose inverse of a general linear system, thus allowing a significant training time reduction.The SLFNN evaluated here uses additive neuron design instead of kernel based, hence random parameter selection[14].The ELM algorithm is given as :

Given a training set $N = \{ (x_i, t_i) | x_i \in R^n, t_i \in R^m, i = 1, .. ,N \}$, kernel function *f(x)*, and hidden neuron $\tilde{N}$.

Step1: Select suitable activation function and number of hidden neurons $\tilde{N}$ for the given problem .

Step 2: Assign arbitrary input weight w_i and bias b_i *i= 1,. .H*

Step 3: Calculate the output matrix *H* at the hidden layer

$$\sum_{i=1}^{\tilde{N}} \beta_i . f(w_i . x_j + b_i) = t_j, j = 1,....N; H\beta = T \quad (3)$$

$$H = f.(w \oplus x + b) \quad (4)$$

Step 4: Calculate the output weight β as :

(5) $$\beta' = H^{\dagger}T$$

where $H^{\dagger}$ is the Moore-Penrose generalized pseudo - inverse of hidden layer output matrix[14].

Statistical Performance Analysis

In this study, 3D GLCM and 3D Gabor filter approach is investigated on a collection of 3D brain from Harvard Surgical Planning (SPL) 10 benchmark image datasets[16] and 35 real time MRI sets using the neural network toolbox of Matlab 2011a.The benchmark datasets included abnormal brain MR images of astrocytoma (AA), low grade glioma (GA) and meningioma (MA).The classification of each voxel in the image to be segmented and computation of the consequent classification probability is performed using extreme learning machine classifier Validation of the classifiers is done by creating classifiers using only part of the expert defined training samples, and then applying the classifiers to those excluded samples to determine how well the classification agrees with the expert's interpretation [10].

The model involved a leave-one-case-out validation approach with different feature attribute subsets to train and test the classifier. The sub-set features from genetic algorithm was given to the ELM classifier in computation of brain tissue categorization. Evaluation based on three validation measures(True Positive (TP), False Positive (FP), True Negative(TN) and False Negative (FN)) were computed:

(6) Sensitivity = T P / (T P + F N)

(7) Specificity = T N /(T N + F P)

(8) Accuracy = (T P + T N) / (T P + T N + F P + F N)

where, TP, TN, FP, and FN are the number of True Positive cases (abnormal cases correctly classified), the number of True Negatives (normal cases correctly classified), the number of False Positives (normal cases classified as abnormal), and the number of False Negatives (abnormal cases classified as normal) respectively. Accuracy is the proportion of correctly diagnosed cases from the total number of cases. Sensitivity measures the ability of the proposed method to identify abnormal cases. Specificity measures the ability of the method to identify normal cases.Table 3 denotes the classification results for cerebrospinal fluid (CSF), White matter(WM) , Gray matter (GM) and Tumor (excluding oedema) for the both texture analysis method on SPL dataset for GA –ELM approach.

In ELM, initially the connection weights of the network are assigned randomly. After using sigmoidal activation function, the weight set is updated by applying a pseudo inverse matrix process. The ELM does not automatically select how many of hidden neurons may work well for the learning process. So the process of employing incremental learning on ELM is done by adding one or more hidden neuron in each iteration.For each time the performance of the learning is tested. The best learning parameters are selected after maximum iterations.

Table 1.GLCM Feature computation for Case 2 (Direction 13, Distance 2)

Energy	Entropy	Contrast	Homogeneity	Mean	Std Dev.
0.8167	3.92	2.634	0.787	0.895	0.23

Table 2. Comparison analysis of classifiers with Feature sub - selection (SPL data)

Texture Analysis	Classifier	Accuracy % w/o Feature selection	Accuracy % with Feature selection
3D GLCM	BPN	77.35	81.55
	GA-SVM	90.5	91.06
	GA-ELM	90.78	93
3D Gabor	BPN	75.12	80.55
	GA-SVM	88.76	90.6
	GA-ELM	89.55	92.8

Table 3.GA-ELM classification result on tumor detection (SPL Data)

Feature Extraction	Parameter	CSF %	WM %	GM %	Tumor %
3D GLCM	Sensitivity	88.95	77.45	70.74	93.06
	Specificity	96	83.88	80.05	97.02
3D Gabor	Sensitivity	88.5	79.60	69.85	95.07
	Specificity	95.78	84.75	76.32	96.78

Discussion and conclusion

Abnormal structures of brain and anatomical brain structures are identified with the 3D MRI image. Focus is on segmenting normal brain into four classes white matter, gray matter , cerobinospinal fluid and tumor. The difference is a binary value for each pixel. It is 0 if the expert and the algorithm classification is same for the given pixel and it is 1 if they differ. The training set is about a few hundred pixels and test region is in the hundred thousand orders of magnitude. The analysis of how the raw intensity input is for the images of thresholded MRI is the most crucial consideration.The intensity values shows an exponential distribution .So a lower threshold below which everything is black and upper threshold above which everything is white is accounted. By considering mean of the object and background gray values as threshold, bias is avoided.Since the original image is used for the segmentation process, the features represent a single pixel not the neighbourhood. Hence the complexity in computational time is avoided.

The design of extreme learning machine as in figure 5 requires setting of one user-defined parameter i.e. number of hidden nodes in hidden layer. A number of experiments were carried out by using the training and test data set with varying the hidden nodes from 1 to 50 .

Results in table 4suggest that extreme learning machine achieves highest classification accuracy of 93 % using 3D GLCM .Table 1 tabulates the values obtianed fro 3D GLCM for SPL data case 2.Figure 2 represents the GLCM feature extarction analysis. But in contrast , maximum real time data accuracy is 90.5% acheived by 3D Gabor filter approach.Figure 4 shows a simple gabor filter case. The raw data requires more normalization and spectral characteristics . Hence Gabor filter works well . The benchmark dataset is normalized with no noise where GLCM achieves better The input data is normalized between values 0 and 1. The random initial weights and bias values range between ±1.The unipolar sigmoidal activation function f (x) = 1 / (1 + e^{-x}) produces better results for the proposed approach. Table 4 represent simulation results on both GLCM and Gabor anlaysis with various classifiers .

Mean and Standard deviation of training and testing dataset were computedd for various initial parameters of hidden neurons. Figure 6 shows the increase in training efficiency with the hidden neurons.The training and the testing efficiency reached its highest value within 30 neurons as in Figure 7.

Table 4.Simulation results (SPL and Real MRI data)

Feature Analysis	Classifier	MSE Error	Training Efficiency % Mean	STD (SPL data)	Testing Efficiency % Mean	STD (SPL data)	Accuracy % (SPL data)	Accuracy % (Real data)	Time (min) (SPL data)	Time (min) (Real data)
3D GLCM	BPN	0.854	82.5	8.62	78.45	9.13	81.55	78.85	15	25
	GA-SVM	0.924	94.4	7.05	86.3	8.25	91.06	85.02	13	30
	GA-ELM	0.971	93.43	7.75	89.06	8.95	93	90.26	3	15.5
3D Gabor	BPN	0.863	82	8.5	79.25	9.40	80.55	82.25	13.5	23
	GA-SVM	0.928	93.8	7.55	91.2	8	90.6	89.2	12	25
	GA-ELM	0.970	92.92	7.80	91.6	8.98	92.8	90.5	2.4	12.4

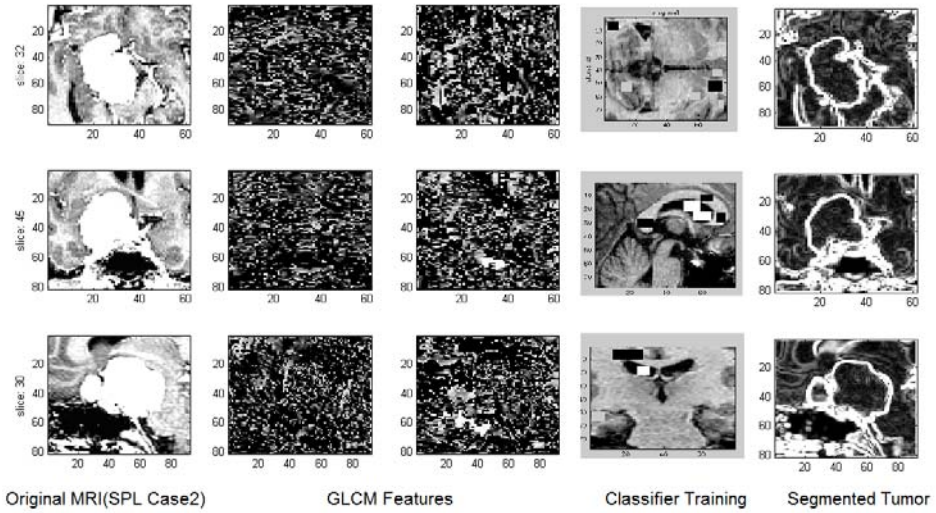

Fig.3. GLCM Feature Extraction Process

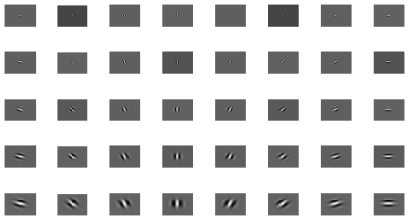

Fig.4. Sample Gabor filters

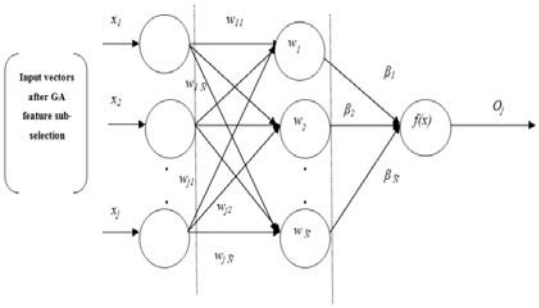

Fig.5. ELM Architecture

The maximum through output performance of the ELM network is achieved with 27 hidden neurons. Preliminary studies report larger number of hidden neurons, which makes the system complex . The hidden neurons parameters is problem dependent . Hence analysis on appropriate selection of the input weights, hidden bias and number of hidden neurons for minimal image data is requisite. The resulting ELM suffers from ill-conditioning due to random selection of input weights and bias . Further research to a simple classification system is necessitated [1].The features selection using wrapper mode using Genetic Algorithm give better results for MRI tumor discrimination towards find of the most appropriate features subset that discriminate at maximum the desired class. To validate the obtained results, the classifier is trained using the whole existing features, and another using the most discriminator features. Table 2 denotes the same.

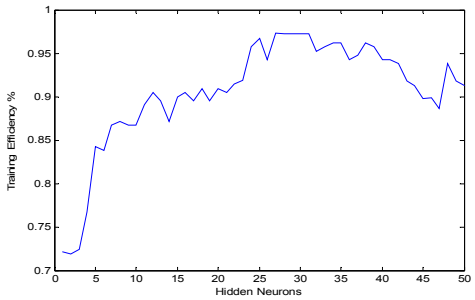

Fig.6. Testing Efficiency of ELM [1]

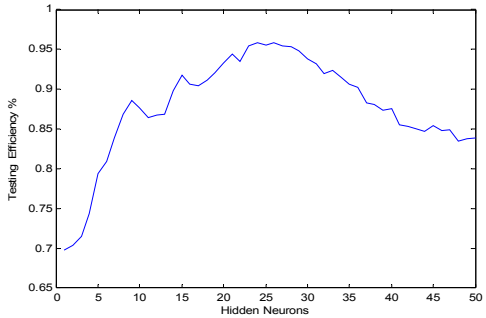

Fig.7. Training Efficiency of ELM [1]

The bank of attributes of the MRI image were obtained using the 3D gabor filters and 3D GLCM features.In the proposed system, GLCM features outperformed the classifier in terms of its accuracy, but requires more computational time. GA selected the most elementary attribute .Table 4 denotes the simulation result of texture analysis on different classifers. In future work further analysis based on the Gabor filter parameters is required to represent a visual cortex analysis. Also study on co-occurrence matrix will articulate and reduce the number of features .The gabor filters provide rotation invariant features and almost approximate the GLCM [5,9].

Thus preliminary studies on texture analysis, characterize and interpret MRI soft tissue images in the context of automated computer assisted diagnosis. The oedema and necrosis part can be further segmented to improve the efficacy of the approach. Volume growth of the tumor part , analysis on larger dataset, multi-modality automation and hardware VLSI implementation to attain a reasonably fast output rate can be investigated. MRI Brain mapping techniques with stereotaxic space' of MRI images can be extended in future.Preliminary investigations of this research and other works[1] reveal the significant requirement of a more simple approach for 3D brain feature extraction model.

Acknowledgments

This work was supported by the Council of Scientific and Industrial Research (CSIR), India. The authors would like to thank Drs. Simon W, Michael K, Arya N, Ron K, Peter B and Ferenc J for sharing the tumor database.The authors also thank PSGIMS&R Hospitals,Coimbatore for MRI specimen database .

REFERENCES

[1] Arunadevi B., Deepa S.N., Brain tumor tissue categorization in 3D magnetic resonance images using improved PSO for extreme learning machine. Progress in Electromagnetics Research B ,49 (2013) , 31-54

[2] Byun H.,Lee S., Applications of Support Vector Machines for Pattern Recognition: A Survey. Proceedings of Int .Work. Pattern Recognition with Support Vector Machines.Niagara Falls, Canada , (2002), 213-236

[3] Chris A. Cocosco , Alex P. Zijdenbos, Alan C. Evans ., A Fully Automatic and Robust Brain MRI Tissue Classification Method . *Medical Image Analysis* , 7(2003),No.4, 513 -527

[4] Chu A., Sehgal C. M., Greenleaf J. F., Use of Gray Value Distribution of Run Lengths for Texture Analysis. *Pattern Recognition Letters,* 11(1990), No.6 , 415-420

[5] Carl Philips , Daniel Li, Jacob Furst , Daniela Raicu., An Analysis of Co-Occurrence and Gabor Texture Classification in 2D and 3D .Proceedings of CARS ,(2008)

[6] Deepa S.N., Aruna devi B.,Second Order Sequential Minimal Optimization for Brain Tumour Classification .*European Journal of Scientific Research*, 64 (2011), No.3, 377-386

[7] Dana Cobzas, Neil Birkbeck , Mark Schmidt , Martin Jagersan., 3D Variational Brain Tumor Segmentation using a High Dimensional Feature Set. Proceedings of Int. Conf .Computer Vision (2007), 1-8

[8] Faraoun K.M., Rabhi A., Data dimensionality reduction based on genetic selection of feature subsets J. Comput. Sci.,6 (2007), 9 -19.

[9] Gao X., Qian Y.,Hui R., Loomes M., Comley R., Barn B., Chapman A., Rix J., Texture based 3D Image retrieval for medical applications. Proceedings of IADIS International Conference e-Health 2010

[10] Good C.D ., Scahill R.I.,Fox N.T., Automatic differentiation of anatomical patterns in the human brain: Validation with studies of degenerative dementias. *Neuroimage,*17 (2002), No.1,29-46

[11] Galloway M. M.,Texture Analysis Using Grey Level Run Lengths. *Comp. Graph. And Image Proc*, 4 (1975) ,172-179

[12] Georgiadis P., Cavouras D., Kalatzis I., Glotsos D., Sifaki K., Malamas M., Nikiforidis G., Solomou E., Computer aided discrimination between primary and secondary brain tumors on MRI: From 2D to 3D texture analysis. *e-Journal of Science & Technology (e-JST)*,(2008), 9-18

[13] Huang G.B., Zhu Q.Y., Siew C.K ., Extreme learning machine: Theory and applications. *Neurocomputing* ,70(2006) ,No.1, 489-501

[14] Huang G.B., Zhu Q.Y ., Siew C.K ., Extreme learning machine: a new learning scheme of feedforward neural networks.Proceedings Int .Conf .Neural networks, Budapest, Hungary ,(2004), 985-990

[15] Haralick R.M., Shanmugam K., Dinstein I.,Textural Features for Image Classification. *IEEE Trans. Syst. Man Cybern*, 3 (1975), 610-621

[16] Michael R., Simon K., Nabavi A., Peter M., Ferenc A., Kikinis R.,Automated segmentation of MR images of brain tumors . *Radiology*, 218 (2001), 586-91

[17] Mahmoud-Ghoneim D., Toussaint G., Constans J.M., de Certaines J.D.,Three dimensional texture analysis in MRI: a preliminary evaluation in gliomas. *Magn Reson Imaging*, 21 (2003),983-987

[18] Mihran Tuceryan , Anil K. Jain , Texture Analysis , Handbook of Pattern Recognition and Computer Vision (2nd Edition), World Scientific Publishing Co., 1998.

[19]Nan-Ying Liang, Paramasivan Saratchandran, Guang-Bin Huang, Narasimhan Sundararajan,Classification of mental tasks from EEG signals using Extreme Learning Machine. *International Journal of Neural Systems*,16(2006),No.1, 2938

[20] Kloppel S., Stonnington C.M., Chu C., Draganski B., Scahill R.I.,Automatic classification of MR scans in Alzheimer's disease. *Brain* ,131(2008),681-689

[21] Karin Junker, Dusan Sovilj, Ingrid Kroncke & Joachim W. Dippner, Climate induced changes in benthic macrofauna–a non-linear model approach. *Journal of Marine Systems* (2012).doi: 10.1016/j.jmarsys.2012.02.005

[22] Kurani AS, Xu DH , Furst JD and Raicu DS. Co-occurence matrices for volumetric data. In : Proc 7th IASTED Int'l Conf on Computer Graphics and Imaging (2004)

[23] Tou J. Y., Tay Y. H., Lau P. Y., Recent Trends in Texture Classification: A Review. Proceedings Symposium on Progress, in Information and Communication Technology,(2009), Kuala Lumpur, 63-68

[24] Zijdenbos A., Forghani R., Evans A ., Automatic quantification of MS lesions in 3d MRI brain data sets: Validation of INSECT. Proceedings Int .Conf. Medical Image Computing and Computer Assisted Intervention. Cambridge MA , USA, (1998) 439-448

[25] Zhu Q.Y., Qin A.K., Suganthan P.N.,Huang G.B., Evolutionary extreme learning machine. *Pattern Recognition*. 38 (2005), No.10 ,1759-1763

***Authors**: B. Aruna devi , Research Scholar, Dept. of EEE,* Anna University , Regional Office - Coimbatore , 641047*, E-mail: arunaamurthy@gmail.com; dr.S.N.Deepa, Assist.Prof, Dept of EEE* Anna University , Regional Office - Coimbatore, 641047*, E-mail: deepapsg@gmail.com*.