Classification of brain tumors using PCA-ANN

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***Abstract*—The present study is conducted to assist radiologists in marking tumor boundaries and in decision making process for multiclass classification of brain tumors. Primary brain tumors and secondary brain tumors along with normal regions are segmented by Gradient Vector Flow (GVF)-a boundary based technique. GVF is a user interactive model for extracting tumor boundaries. These segmented regions of interest (ROIs) are than classified by using Principal Component Analysis-Artificial Neural Network (PCA-ANN) approach. The study is performed on diversified dataset of 856 ROIs from 428 post contrast T1-weighted MR images of 55 patients. 218 texture and intensity features are extracted from ROIs. PCA is used for reduction of dimensionality of the feature space. Six classes which include primary tumors such as Astrocytoma (AS), Glioblastoma Multiforme (GBM), child tumor-Medulloblastoma (MED) and Meningioma (MEN), secondary tumor-Metastatic (MET) along with normal regions (NR) are discriminated using ANN. Test results show that the PCA–ANN approach has enhanced the overall accuracy of ANN from 72.97 % to 95.37%. The proposed method has delivered a high accuracy for each class: AS-90.74%, GBM-88.46%, MED-85.00%, MEN-90.70%, MET-96.67%and NR-93.78%. It is observed that PCA-ANN provides better results than the existing methods.**

***Keywords*—Gradient Vector Flow (GVF), brain tumor classification, feature extraction, Principal component analysis (PCA), regions of interest (ROIs)**

I. INTRODUCTION

MR images obtained from different excitation sequences (T1, T2, post contrast T1 and FLAIR) provide texture and intensity information of brain tumors. The tumor on post contrast T1-weighted sequences is enhanced by inducing 0.15-0.20 mMol/kg of contrast material (Gadolinium) in the patients. Therefore, tumor is better visualized on these sequences as compared to other MR sequences. Tumor or region of interest (ROI) on MR image is marked manually or by computer aided techniques (CATs). CATs consist of automatic and semi-automatic segmentation methods [1-6]. However, automatic segmentation methods require high computational time whereas ROI is user defined in the semiautomatic segmentation methods. Therefore, computational time is less for these methods. The segmented ROIs are then classified by pattern recognition techniques. Some researchers have differentiated between two classes-normal (non-tumorous) and abnormal (tumorous) tissues [7] [8]. Selveraj et al. differentiated normal and abnormal regions from 1100 regions of interests (ROIs) using least square support vector machine (SVM) achieving an accuracy of 98% and 96% respectively [7]. Similar experiment is performed by El Dashan et al. on a dataset of 80 ROIs using PCA for feature reduction and FP-ANN classifier was used. An accuracy of 97% and 98% is obtained [8].

Multiclass classification models for classifying brain tumors are proposed by [9] [10] [11]. Zacharaki et al. [9] performed experiments on 98 images for classifying low grade gliomas, Glioblastoma Multiforme and Glioblastoma Multiforme Accuracy obtained for each class is: Metastasis-91.7%, Low-grade glioma-90.9%, Glioblastoma Multiforme-41.2% and Glioblastoma Multiforme-33.4%.Similar studies were proposed by Georgiadis et al. [10] [11]. Metastases, Meningiomas and Gliomas are classified in his two studies using Least Squares Features Transformed-Probabilistic Neural Network (LSFT-PNN) classifier. This pattern recognition system uses textural features which improves brain tumor classification accuracy from routinely taken MR images. The Probabilistic Neural Network (PNN) is a non-parametric feed-forward neural network classifier having comparatively less computational load than other classifiers and is fast in training [12]. LSFT provides better classification as patterns of each class are clustered around pre-selected points therefore; training patterns are transformed by non-linear least square function and are then fed to PNN [13]. In the first study, experiment is performed on 75 images achieving an accuracy of 87.50% for Metastases, 95.24% for Meningiomas and 96.67% for Gliomas. In the second study, dataset of 67 images is considered. 95.24% and 93.48% respectively is achieved between primary and secondary tumors. In the second stage, primary tumors are classified delivering an accuracy of 100% for Meningiomas and 88.89% for Gliomas.

Literature studies have revealed that there are very few studies for segmenting and classifying brain tumors along with normal regions. Generally Meningiomas, Gliomas and Metastatic tumors are classified. Moreover, the earlier methods have used very small datasets for classification. There has been no attempt to classify child tumors (Medulloblastoma) and to separate Astrocytoma from Glioblastoma Multiforme due to their close resemblance. Very low accuracy has been obtained specifically in identification of Glioblastoma Multiforme (less than 50%).

In this paper, an attempt has been made to overcome the above limitations by using Principal Component Analysis-Artificial Neural Network (PCA-ANN) approach. Tumors (ROIs) are segmented by Gradient Vector Flow (GVF) model. 856 ROIs are extracted from 428 post contrast T1 MR images. 218 intensity and texture features are extracted from these ROIs and PCA is used for dimensionality reduction. ANN is then used to classify six classes-5 classes of brain tumors and a normal class. These classes are: Primary tumors- AS, GBM, child tumor-MED, MEN, secondary tumor-MET and normal

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region (NR). An interactive CAD system is developed to assist radiologists in multiclass brain tumor classification. Hence, this approach is named as PCA-ANN.

This paper is organized in the following main sections. Section 2 provides the detail method used. In Section 2, marking of tumor boundaries by GVF, feature extraction from ROIs, feature selection using Principal Component Analysis (PCA) and the classifier (ANN) modules are discussed. Dataset is illustrated in Section 3. In Section 4, experimental results and discussions are given. The paper is concluded in Section 5.

II. PROPOSED METHOD

The proposed system is developed to assist radiologists in segmenting and classifying brain tumors on MR images as shown in Figure.1. The system consists of four modules: (i) Gradient Vector Flow (GVF)-for marking ROIs, (ii) feature extraction from ROIs (iii) feature reduction using PCA (iv) classification module using ANN. The selected features are used as inputs to ANN.

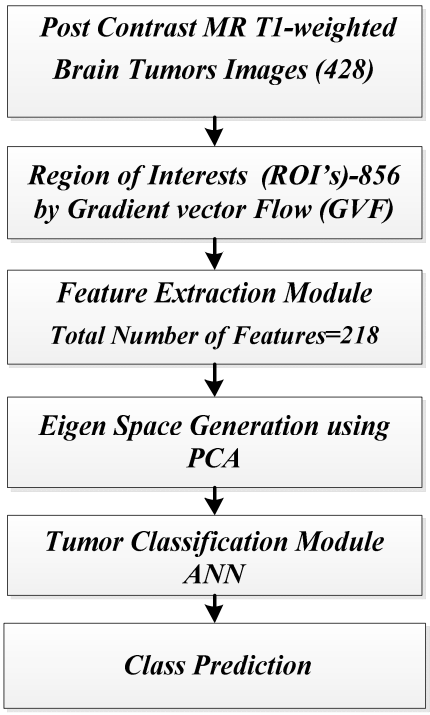

Figure.1:Flow diagram of the proposed system

A. Gradient Vector Flow (GVF)

In the proposed system, GVF is used to extract tumor boundary. GVF [6] [14] is a parametric active contour given by

$$C(s) = (x(s), y(s)), \qquad s \in [0,1] \tag{1}$$

where *s* the localization parameter, denoting a point on GVF snake. After initialization, GVF snake C(s) deforms to minimize snake energy which is the sum of internal and external energies. These energies are defined from contour shape and image characteristics. GVF uses an edge map *f* to generate spatially distributed vector field as:

$$\mathbf{v}(x,y) = (u(x,y), v(x,y)) . \tag{2}$$

Edge map increases towards image edges. It is derived from the image and is taken as the quantity along which negative gradient of the contour deforms. Prince et al. used outputs of negative of Laplacian and Laplacian of Gaussian as an edge map to guide the contour towards the edge in an image. GVF is generated by minimizing the energy functional:

$$E_{GVF} = \iint (\mu(u_x^2 + u_y^2 + v_x^2 + v_y^2) + |\nabla f|^2 |v - \nabla f|^2) dxdy \tag{3}$$

where, μ is the blending parameter and ∇f is the gradient of the edge map. μ determines the sensitivity of GVF to edges present in images, its value can adjusted to surpass the effect of weak edges (due to noise present in image) on final segment. More the value of μ, more is GVF tolerant to false edges. During experiments the value of μ has been taken between 0.05 and 0.3 depending on quantity of noise in image and quality of segment retrieved. This equation is solved using calculus of variations in the form of Euler Lagrange equations.

$$\mu\nabla^2 u - (u - f_x)(f_x^2 + f_y^2) = 0$$
$$\mu\nabla^2 v - (v - f_y)(f_x^2 + f_y^2) = 0 \tag{4}$$

where ∇^2 is the Laplacian operator. These are solved iteratively by assuming u and v as function of both space and time in the following ways:

$$\mu\nabla^2 u(x,y,t) - (u(x,y) - f_x(x,y)) \tag{5}$$
$$(f_x^2(x,y) + f_y^2(x,y)) = 0$$
$$\mu\nabla^2 v(x,y,t) - (v(x,y) - f_y(x,y)) \tag{6}$$
$$(f_x^2(x,y) + f_y^2(x,y)) = 0$$

.

The GVF snake deforms until it reaches some optimum solution i.e. the desired boundary of the tumor. The ROI marked within the tumor region and the final boundary extracted is shown in Figure.2 (a) and Figure. 2(b) respectively.

Figure.2(a): ROI marked within the tumor region

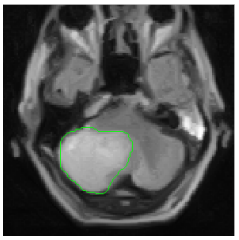

Figure.2(b): Final boundary extracted (in green)

B. Feature Extraction

218 intensity and texture features are extracted from tumors and normal regions. These features are discussed below:

1.) Gray Level Co-occurrence Matrix: Four different features namely Contrast', 'Homogeneity', 'Correlation' and 'Energy' for four different offsets are calculated, contributing 16 features in feature pool [15].

2.) Laplacian of Gaussian (LoG): Four different values of Gaussian widths viz. (0.25, 0.50, 1, and 2) for LoG filters are

considered, and are convoluted with the input image. Four statistical parameters i.e. mean, standard deviation, skewness and kurtosis for the LoG filter output in the ROI region are retrieved thereby contributing 16 features in feature pool.

3.) Directional Gabor Texture Features: The λ (in pixels) and θ (in degrees)are varied for five different values viz. (2√2,4,4√2,8,8√2) and θ (0°, 22.5°, 45°, 67.5°, 90°) resulting in 25 different Gabor filter features [16]. Four statistical parameters i.e. mean, standard deviation, skewness and kurtosis are extracted for each filter output in the marked ROI and are taken as 100 features in the feature bank.

4.) Rotation Invariant Circular Gabor Features: At five values of λ (in pixels) viz. (2√2, 4, 4√2, 8, 8√2) and two values of ψ i.e. 0°and 90°, 10 rotation invariant circular Gabor features are retrieved [17]. Four statistical parameters i.e. mean, standard deviation, skewness and kurtosis are extracted for each filter output in the marked ROI and are taken as 40 features in the feature bank.

5.) Rotation invariant Local Binary Patterns: Intensity pattern in tumor region is modeled using histograms. The proposed system makes use of range filter, standard deviation filter, and average filter with neighborhood of 7x7 on three LBP images of radii -1, 2 and 4 pixels. Thus nine filtered images are obtained. Four statistical features are obtained from these images and 36 features are added to the feature bank [18]

6.) Intensity based features: Four intensity-statistical parameters namely: mean intensity, standard deviation, skewness and kurtosis from the histogram of an image within the tumor segment are calculated. Apart from the four parameters, mean entropy of the ROIs is also considered. 10 intensity features are added in the feature bank

C. Feature selection using PCA

The purpose here is to obtain an optimal subset of features which produce the best possible results. The proposed system makes use of PCA for reduction of dimensionality of the feature space. The complete dataset has been used to compute Eigen space for the features. The optimum numbers of Eigen features selected are 49. The complete dataset has been used to compute Eigen space for the features.

PCA forms a linear transformation A_n^T, transforming a random vector $X \in \Re^m$ to a random vector of lower dimension $Y \in \Re^n, m > n$. Here m and n are significantly less than the number of samples where m is the number of total input features (m = 218) and n are the retained Eigen features (n = 49). The input random vectors X have zero mean and a covariance matrix $\sum$. The output (reduced dimensions) is obtained as $Y = A_n^T X$, where size of A_n^T is $n \times m$. The whole training data set has been used for formation of covariance matrix. If the input data is initially of m dimensions, the covariance matrix is of size $m \times m$. This covariance matrix is used to construct Eigen feature space and m Eigen vectors. The dimensions (m) are computed in decreasing order of their Eigen values. The transformation A_n^T is obtained by retaining top n Eigen vector in terms of Eigen values thus forming transformation matrix A_n of size $m \times n$. Thus the output feature vectors are obtained by projecting it to a new coordinate system and retaining the dimensions with maximum variations. The numbers of Eigen features retained are estimated by hit and trial method [19] [20].

D. Classification Module

Multi-Layer Perceptron (MLP) is the Artificial Neural Network (ANN) based supervised learning algorithm used for solving regression problems [19] [20]. Neural network in the proposed system is analyzed for estimation of the number of Eigen vectors to be retained for best classification capability. Gradient Descent Back-Propagation with momentum (GDBPM) algorithm is used for estimating weights (training phase), momentum weight and bias based learning. The proposed network uses the momentum constant as 0.8 and learning rate of 0.02. To avoid over-training and to improve generalization of the network, 10-fold cross validation is used during network training. The network topology is decided by hit and trial method. It is observed that 18 neurons in hidden layer deliver a reasonable tradeoff between accuracy and speed.

III. Dataset and Software Implementation

A. Dataset

In the present study, 856 ROIs are marked from 428 brain tumors MR images. These images are acquired from 55 patients at Department of Radiodiagnosis, Postgraduate Institute of Medical Education & Research (PGIMER), Chandigarh, India over the time period January 2010 to May 2011. These MR images include -118 AS, 59 GBM, 97 MED, 88 MEN, 66 MET and 428NR. The number of ROIs for NRs are taken significantly large than the malignant regions to well recognize highly varying anatomical regions. All images are obtained using the same MRI equipment (Siemens Verio, Erlangen Germany, and 3Tesla MR Scanner). These tumors are graded and manually segmented by the radiologists based on their knowledge on visual image interpretation of brain tumors, clinical history of the patient, and disease confirmation by the biopsy/dynamic helical CT/MRI/pathological examinations. 40% of the dataset is used for training, 10% is used for validation and 50% is used for testing.

B. Software Implementation

Proposed method is implemented in MATLAB 8.0 and is tested on various brain tumor MR images of size 256×256. The experiments are performed on PC having Intel ™ Core 2 Duo ® 2.0 GHz processor with 3 GB RAM.

IV. Experimental Results

A. Evaluation Metric

The results of PCA-ANN classifier are given in Table 1. The basic data structure used for evaluation is Confusion Matrix. The performance of the proposed method is analyzed in terms of individual class accuracy and overall classification accuracy. Given a Confusion Matrix as shown in Table 1, in context of brain tumor classification system:

Class (i) = Number of instances of class (i) in dataset

Individual Class Accuracy for ith class = TP (i) /class (i)
where, TP(i) is correctly classified instances of class (i)
Overall Classification Accuracy=

$$(\sum_i TP(i) / \sum_i class(i)) * 100$$

TABLE 1 CONFUSION MATRIX (ANN)

		Ground truth Class (assigned by Radiologist)					
		AS	GBM	MED	MEN	MET	NR
Class Predicted	AS	49	2	0	1	0	2
	GBM	3	23	2	0	0	0
	MED	0	0	34	0	0	6
	MEN	0	0	0	39	0	3
	MET	0	1	1	0	29	1
	NR	2	0	3	3	1	181
Individual Class Accuracy (%)		90.74	88.46	85.00	90.70	96.67	93.7
Overall Classification Parameters							91.97%

B. Results and Discussions

The overall accuracy and individual class accuracy of PCA-ANN classifier (Table 1) is 91.97%. It is noticed that an increment of about 23% is observed in overall accuracy by using PCA for feature reduction. The proposed method delivers high accuracy for each class. The accuracy obtained for each class is: AS-90.74%, GBM-88.46%, MED-85.00%, MEN-90.70%, MET-96.67% and NR-93.78%. Direct comparison with earlier methods has not been performed as dataset is not a standard one and has not been used by the other methods in the literature. The accuracy obtained by earlier studies for class 2 lies in the range of 42% whereas the proposed method has delivered an accuracy of 88.46%. For class 4 i.e. MEN, PCA-ANN has delivered an accuracy of 90%. In case of class 5 (MET), from the previous studies it is observed that the accuracy obtained lies is in the range of 87% to 95 % but with the proposed method, the accuracy obtained is 96.67 %. Class 1(AS), class 3(MED) of child tumors and class 6 (NR) have not been considered in the earlier studies. It is observed from the experimentation that the selection of texture and intensity features by PCA and classification by ANN have given better results for all classes. The proposed method performs the broad classification of brain tumors. For more crisp classification, dataset comprising of subclasses of a tumor e.g. for Astrocytoma class both low grade and high grade Astrocytoma will be collected in the future and the proposed method will be tested on a wide diversified dataset. However, data collection may take a long span of time.

V. CONCLUSION

In this paper, GVF is used for extracting tumor boundaries (ROIs). PCA for reduction of dimensionality of the feature space and multiclass classification of brain tumors using ANN is proposed. The performance of PCA-ANN is evaluated for dataset of 856 ROIs from 428 images. The experiment performed consists of primary tumors and secondary tumors which differ in every aspect in their appearance, location, size and shape. High individual class accuracy (Table 1) is achieved. Further, PCA-ANN has delivered an overall accuracy of 91.7%. The study reveals that the proposed method has delivered better results than the earlier methods and has been tested on more diversified dataset.

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