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An efficient MRI processing technique for diagnosing brain tumor and allied nervous diseases

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Abstract—.: **Brain tumor is a dreaded disease which is of wide occurrence in humans. Its detection in the beginning can provide better treatment facilities to the patient. Decision about the ideal nature of treatment for any pathology including tumor depends on the information provided by advanced imaging techniques such as Magnetic resonance imaging (MRI). Brain tumor segmentation is an important technique that is used for the diagnosis of brain tumor and allied nervous diseases. Computer aided detection of tumor often provides highly accurate results than manual segmentation..The intensity of tumor differs from patient to patient and because of this the exact tumor locations of lesions appear blurred in MRI images. The size of tumor also varies and it occurs at different regions of the brain. . Brain cells are made up of watery substances and some fluid matter. Addition to these liquids the cells also allow the blood flow and most importantly the oxygen intake. The flow of these fluids create small noises which can only be detected by sophisticated scanning technologies such as MRI.A large number of techniques have been developed for segmentation of tumor of which most of them failed during the presence of edema and noise .In order to overcome these issues ,here we are using a technique namely Local Independent Projection-Based Classification(LIPC).In this method training samples are obtained from patients and they are arranged into different groups of classes to construct different dictionaries. Testing samples are then projected onto these using Local Anchor Embedding (LAE). Spatial contextual information is an additional contextual feature included to improve the performance of image segmentation. Experiments have been conducted using MRI images collected from various sources and were observed that the results obtained were highly accurate.**

Index Terms—**Image segmentation, Local Independent projection-based classification (LIPC), Local Anchor Embedding (LAE), Magnetic Resonance Imaging (MRI)**

I. INTRODUCTION

A brain tumor is a growth of abnormal cells in the brain. Cells are the basic structural and functional units in living organims.When a body is working normally, new cells form only to replace the damaged or the old cells. When cells grow abnormally when they are not required, they can accumulate to form tumor. Brain tumor cause damage because they can either place pressure on normal parts of the brain or spread into those areas. The two main types of tumors are primary brain tumor and secondary brain tumor. If the tumor originates in the brain, it is called as primary brain tumor. Primary brain tumor can be malignant or bening. A metastatic brain tumor is also called a secondary brain tumor. It stats as a cancer in some other parts of the body and ultimately affects the brain. The National Cancer Institute (NCI) uses a grading system to classify tumors based on their characteristics.
Tumors of the central nervous system are classified by World Health Organisation (WHO) as Anaplastic astrocytoma, Astrocytoma, , Gliosarcoma, Hemangiopericytoma, Medulloblastoma, Medulloepithelio ma, Trilateral retinoblastoma, Choroid plexus carcinoma etc. Fig.1 and Fig.2 shows the primary and secondary brain tumor.

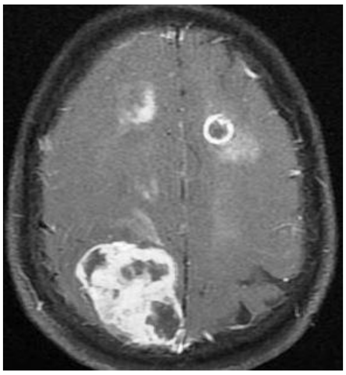

Fig.1.Primary brain tumor

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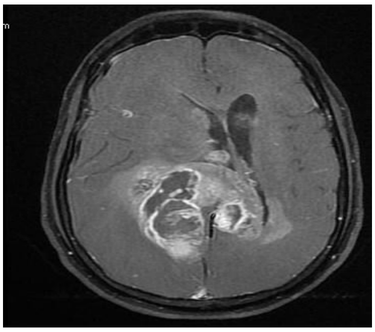

Fig.2.Secondary brain tumor

Even though there are various techniques in the field of medicine such as CT scans, angiogram etc for detecting tumors, the best type of imaging technique to diagnose most types of brain tumors is MRI. It is a scanning device that uses magnetic fields and dipoles to obtain the images of the brain on the film.MRI detects images signals emitted from normal and abnormal tissues providing clear images of almost all the tumors. Particularly, MRI is useful in neurological (brain), musculoskeletal, and oncological (cancer) imaging because it offers much greater contrast between the diverse soft tissues of the body than the computer tomography (CT).Thus image processing is a significant tool that can be effectively used so as to examine anatomical structures. The images obtained during the examination can act as valuable source of information for the physician. There are two types of images namely T1 dependent and T2 dependent. These images can display the structure of the brain effectively. The gray matter and the tumors appear black in T1 dependent images while the white matter appears gray in colour. The reverse is the case in T2 dependent images. When the pathological structures are poorly visible or the boundaries of the tumor are difficult to define, the obtained image requires computer processing. Various methods and algorithms are used for processing the image of which segmentation is an important one. Image segmentation is the process of partitioning a digital image into multiple segments. It assigns a label to every pixel in an image such that pixel with the same label share certain characteristics. Segmentation helps to simplify and change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries in images.

A wide variety of segmentation techniques have been developed in recent years for detecting tumors. Unfortunately most of the techniques had their own critical drawbacks. In article [1] ,the author proposed a segmentation technique using K-means algorithm followed by object labeling algorithm. Even though this technique was useful in detecting tumor to a certain extent, it failed during the presence of edema which was often misinterpreted as tumor.In article [2],the author proposed a technique so as to find the bilateral symmetry of human brain from MRI.Here the anatomical regions of the brain are segmented isolate the two halves of brain and to investigate each half for the presence of asymmetry of anatomical regions in MRI. In article [3], author proposed a region growing approach for detecting tumor. This technique was quite simple and could properly locate the tumor edges but it was highly sensitive to noise which was a major drawback of the region growing method. The region growing method enables precise tumor detection; however, the selection of an appropriate homogeneity criterion is a prerequisite for correct segmentation. Also the Edema was often misinterpreted as tumor in this technique. In article [4] ,bilateral symmetry analysis is used so as to detect tumor. This analysis for tumor detection is based on the principle that tumors that appear in one of the cerebral hemispheres can cause asymmetry between the left and the right cerebral hemispheres .The amount of this asymmetry is calculated and the tumor can roughly be located. However, accurately finding the mid sagittal plane is a challenging and time consuming task. Also this technique fails when the tumor is located across the mid sagittal plane. In article [5] , the author proposes a technique for detecting tumor based on cohesion based self merging algorithm. Even though effective, this method cannot keep all the features of the original data set .In article [6], the author proposed a content based active contour model for brain tumor segmentation. In article [7], the author presents a region based fuzzy clustering which is used for initial segmentation of tumor then result of this is used to provide initial contour for GVF snake model, which then determines the final contour for exact tumor boundary for final segmentation .This method failed in presence of noise.

In this paper segmentation is done using Linear Independent Projection- based classification (LIPC). Some preprocessing steps are performed on the images so as to remove the unwanted noise components and to obtain the required features.We performed a series of experiments using this segmentation technique and the results obtained were satisfactory.

II PROPOSED METHOD

The proposed method makes use of a new technique called Local Independent Projection –Based Classification (LIPC).Using this technique each voxel is classified into different classes. Preprocessing is applied for a given data set. Training and testing are then implemented. The purpose of this is to remove the unwanted features and to select the required features from the specified data set. The proposed method is embedded on a multiresolution framework so as to reduce the computational cost. By using the LIPC method we can implement dictionary construction, locally linear representation, and classification score computation. The proposed method with the learned softmax regression model was much higher than that of the proposed method without the learned softmax regression model for the real data groups. We used a patch-based feature, so the image intensity distribution had a strong correlation with the sample distribution. The distribution of the training data in each sub manifold is an important clue for the classification task and can bring discriminative information when classifying a testing sample. Thus, the proposed method with a learned softmax regression model is more applicable for data with complex distribution than data without the learned softmax regression model. The segmented images are classified efficiently and effectively by

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using proposed LIPC method and could effectively detect tumor and its location and area of spread. Fig.3 shows the block diagram of the proposed method. The proposed method basically consists of four steps namely pre-processing, feature extraction, segmentation using LIPC and post processing .

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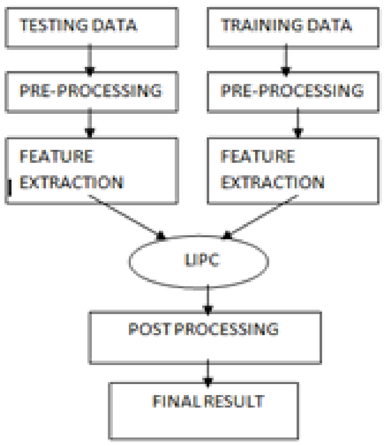

Fig3.Block diagram

The proposed method basically consists of four steps namely pre-processing, feature extraction, segmentation using LIPC and post processing.

A .PRE-PROCESSING

Pre-processing is done on the image initially so as to improve its quality of visualization. After the digital image has been captured and prior to initiating algorithm applications, each image should be evaluated with regard to its general characteristics including noise, blur, brightness, background intensity variations etc. This task is effectively accomplished through pre-processing step. Different types of noises are likely to occur on the image for which there are appropriate noise filtering methods.

B. FEATURE EXTRACTION

As the image intensities in MRI images do not have a fixed meaning and widely vary within or between subjects, image in homogeneity correction and intensity normalization should be performed before extracting features to represent samples. Initially N3 algorithm is used so as to remove the bias field artifacts from the image. Intensity values at 1% and 99% are computed for brain region including tumors, edema and brain tissues.The two values are then used to linearly scale the voxel intensities to range [0,100].In this paper we are extraction the feature based on a patch based technique. First we obtain the intensity values in a patch around a voxel,v ,and it is rearranged as a feature vector.

C .LIPC SEGMENTATION

A series of experiments were made on testing and training brain tumor image data. For training a complete tumor was divided into tumor core and edema part in real patient data.The proposed method was evaluated using a five –fold cross validation fashion. . All experiments were repeated five times, and the final results were reported as the mean and standard deviation of the results from the individual runs. We used 64 images for training and 16 images for testing. . To evaluate the proposed method for the testing data, the training data was used to train classifiers for different tissues. . The segmentation results of the testing data were uploaded to the online evaluation platform and were evaluated automatically.

D. MULTI RESOLUTION NETWORK

We have used a multiresolution network in the proposed method so as to increase the robustness and to reduce the computational cost. For a multiresolution framewok with n levels, classification initiated from the coarsest M_{n-1} to the finest M_0 so as to classify the voxel into different classes. The classification scores for all voxels in coarser levels were up-sampled to initialize the classification for a finer level.This was achieved using trilinear interpolation method.At each level a confidence threshold αt was defined.This is to determine the voxels that can be directly labeled and the ones that require further processing. The remaining voxels with $yi \in [0, 1 - \alpha]$ were fed into the proposed classifier for an accurate classification. This procedure was repeated until the resolution of the original level M_0 was reached.

E. CLASSIFICATION USING LIPC

A softmax regression module is used for reconstruction error norm in order to achieve classification scores. Classification accuracy was tested using learned as well as without learned softmax regression model. Accuracy was seen high for learned softmax regression model for real data groups ($n<0.02$).However the classification accuracy using learned and without learned softmax regression model was found to be same for synthetic data groups($n>0.6$).This shows that the intensity distribution is complex in real data groups than in synthetic data groups. The intensities of the three classes could be easily separated in synthetic data with high-grade gliomas, whereas the intensity distribution of the three classes largely overlapped with one another in the real data groups. . The distribution of the training data in each submanifold provides important details for the classification task and can bring discriminative information when classifying a testing sample. Thus the learned softmax regression model was suitable for data with complex distribution.

F. POSTPROCESSING

Inorder to post process the classified edema regions, we make an assumption that the edema regions are located near the tumor core regions. So according to this each classified edema region will have a voxel near the classified tumor region within a short distance. Connected component algorithm and mathematical morphology are used to refine the

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classified edema regions. The four steps involved in this are as follows:

STEP 1 : A binary image is formed using the classified edema regions

STEP 2 : The binary image so formed is used as input to the connected component algorithm. Using this some individual edema regions are created.

STEP 3 : Each individual edema region is dilated with a small structuring element and is compared against the classified tumor region

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STEP 4: Here the number of voxels shared by the dilated edema regions and the classified tumor regions are noted. The dilated edema regions that share at least one voxel with the classified tumor regions are considered as valid. The edema regions' from thse valid regions are considered as final edema classifications and the rest are discarded.

III EXPERIMENTAL RESULTS

The validity of brain tumor segmentation is an important issue in medical image analysis as it has a direct impact on surgical planning and other modes of treatment. The proposed technique was applied on different MRI images having brain tumor collected from various medical centers and the result obtained was found to be highly satisfactory. The result obtained from this technique was found to be far more superior when compared to the results obtained from other segmentation techniques including K-means algorithm. The proposed technique also enables to know the area of spread of the tumor and the region affected by tumor.Fig.4.shows the detected tumor from MRI image using LIPC segmentation. The area of spread as well as the region affected are also shown.

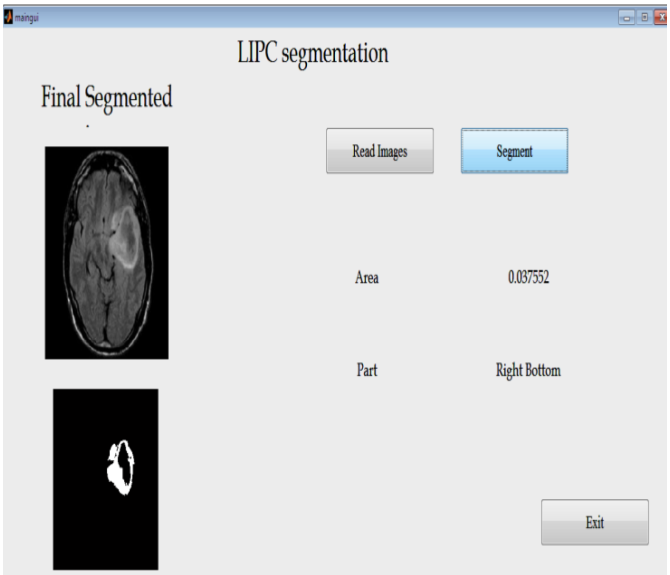

Fig.4.Tumordetected using LIPC Segmentation

IV CONCLUSION

It is to be noted that world over, in the medical field, brain tumor is causing embarrassing catastrophes. In view of this dreaded disease, several techniques have been developed for detecting brain tumor from MRI images. The method proposed in this paper is certainly an effective one which makes use of Linear Independent Projection –based Classification for the accurate detection of tumor.. White matter, grey matter, cerebrospinal fluids can also be detected using this segmentation. This technique was tested on real MRI images collected from various medical centers and the results were highly accurate.

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REFERENCES

[1] M. M. Ahmed and D. B. Mohammad, "Segmentation of brain mr images for tumor extraction by combining kmeans clustering and perona-malik anisotropic diffusion model," IJIP, pp. 27-34, 2008

.

[2]Samir K. Bandyopadhyay," Finding Bilateral Symmetry of the Human Brain from MRI", Journal of Global Research in Computer Science, Volume 2, No. 2, February 2011,pp. 33-34.

[3]PREETHA M. M. S. J., SURESH L. P., BOSCO M. J., Image segmentation using seeded region growing, Computing, Electronics and Electrical Technologies (ICCEET), International Conference, ISBN:978-1-4673-0211-1, 2012, pp. 576-583.

[4] JIAO Feng, FU Desheng, BI Shuoben" Brain Image Segmentation based on Bilateral Symmetry Information" 978-1-4244-1748 2008 IEEE

[5] Subhranil Koley and Aurpan Majumder 'Brain MRI Segmentation for Tumor Detection using Cohesion based Self Merging Algorithm' 978-1-61284-486-2/111$26.00 ©2011 IEEE

[6] J. SACHDEVA,V.Kumar,I.Gupta,N.Khandelwal and C.K.. Ahuja, "A novel content based active contour model for brain tumor segmentation," Magn.Resonance Imag.,vol.30,no5,pp,694-715,jun 2012

[7] 0. G. Moonis, J. Liu, J.K. Udupa, and D.B. Hackney. Estimation of tumor volume with fuzzy-connectedness

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segmentation of MR images. American Journal of Neuroradiology, 23:352–363, 2002

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