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Comparative Study of De-Noising, Segmentation, Feature Extraction, Classification Techniques for Medical Images

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ABSTRACT— Early identification and classification of brain tumors play a major role in the diagnosis of tumors. This paper attempts to take the study of various pre-processing, segmentation, feature extraction and classification techniques which are needed to efficiently extract the tumor region and classify them according to their grades from the MR brain images. Pre-processing of medical images is needed because the image may be degraded by noise either during transmission or acquisition. Filtering techniques are effective only if they preserve edges during pre-processing. Tumor region is extracted from the MR brain images using the various segmentation techniques. Segmentation is effective if it includes the spatial information as well as the global intensities of the image. Since the pixels in the images are highly correlated, statistical features are best suited for the optimistic classification. The various classifiers and their accuracy in terms of sensitivity, specificity for the classification of tumors are studied for the selection of appropriate classifier.

KEYWORDS— Classifier, Feature Extraction, Pre-processing, Statistical Features, Tumor Extraction

I. INTRODUCTION

Brain tumor is one of the major reasons for death among the people. Tumors can be of either benign which are cancerous or malignant which are non-cancerous. Identification of tumor at its earliest stage will be helpful for the patients in their diagnosis. There are various medical imaging techniques to examine the presence of tumor. The major modalities are X-ray, Computed Tomography, Ultrasound and Magnetic Resonance Imaging. Among all these techniques, MRI shows the clear picture of tumor present in brain. The less

intervention of human for the detection of brain tumors is done through the automation of system for its detection. The image acquired through MRI modality may be subjected to some sort of noises. Before identifying the tumor region from brain MRI, it should be free from noises.

Effective segmentation is carried out to extract the tumor region from the noise free brain MRI. Segmentation algorithm is said to be effective only if it considers each and every pixels present in the image. In order to classify the tumors based on their grades, their features are to be extracted. The features can be of general features or based on the applications the features may vary. The shape of the tumor is not the effective feature for classification since tumor has no specific shape. Hence the statistical features which are dependent on the varying intensity of the pixel are the optimal feature for the design of efficient classifier.

Classification is one of the most frequently encountered decision making tasks. Classification is the process of assigning the object to a predefined group or class based on a number of observed attributes related to that object. The organization of the paper is as follows. After the introduction, we present the noise models and their removal using filtering techniques in Section II. Then the parameters for the better segmentation for the tumor detection are survey and discussed in Section III.

Feature extraction as well as appropriate feature selection for the classification of tumor grades is dealt in Section IV. The various classifiers and their fundamental issues are explained in Section V.

II. LITERATURE STUDY

A. Pre-processing

Image quality is degraded by signals which are not relevant to the image and hence it gets distorted. Noise can be of many forms: Gaussian noise, Speckle noise, Salt and Pepper noise. These noises can be defined by their probability density functions. Gaussian noise model is defined as

$$H(g) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(g-m)^2 / 2\sigma^2} \tag{1.1}$$

where g is the gray level of the image

m is the mean value

σ is the standard deviation

Speckle noise model is given as

$$H(g) = \frac{g^{a-1}}{(\alpha-1)!\,a^{\alpha}} e^{\frac{-g}{a}} \tag{1.2}$$

where g is the gray level

Wei Xu and Klaus Mueller (2010), suggested the use of non-linear filtering techniques such as Bilateral filter, Non-Local Means filter, Trilateral filter for the removal of noise in CT scan images [15]. Bilateral filter used two functions: closeness function and similarity function. Closeness function is used to average the nearby pixel values and similarity function is used to exclude dissimilar pixels. The bilateral filtering can be specified as,

$$F(x) = \frac{\sum\limits_{y \in W} g(y)\,\mathrm{s(h(x), h(x+y)).h(x+y)}}{\sum\limits_{y \in W} g(y)\,s(h(x), h(x+y))} \tag{1.3}$$

where W is the window centered at the pixel x

y and x are the spatial image pixels

g is the closeness function

s is the similarity function

The closeness function is given as,

$$g(y) = e^{\frac{-\|y\|^2}{2\sigma_d^2}} \tag{1.4}$$

where σ_d controls the amount of smoothing

The similarity function is specified as,

$$s(h(x), h(x+y)) = e^{\frac{-(h(x)-h(x+y))^2}{2\sigma_r^2}} \tag{1.5}$$

where σ_r controls the amount of smoothing

Non-Local Means (NLM) is a non-linear filter that replaces the pixel located at x with a mean of the pixels whose Gaussian neighborhood looks similar to the neighborhood of x. Bilateral Filter do not preserve image gradients and to overcome this, trilateral filter is used.. The proposed NLM filter is a non-linear filter that replaces the pixel located at x with a mean of the pixels whose Gaussian neighborhood looks similar to the neighborhood of x. This filter removes the spatial smoothing but increases the dimension of range filter. Such a change yields more accuracy to smoothing but it increases time complexity. The failover of this technique is that the images need an average of 30 iterations to regularize the CT image. The efficiency of the filtering technique was not evaluated with the parameters.

Bhausaheb Shinde et al. (2012) performed the comparative study of various filtering techniques to remove the speckle noise present in the MR brain images [11]. Median filter uses the middle pixel value to replace the remaining pixels present in the window. This is used to remove the outlier noise present in the MR images. The formula to calculate the middle pixel value in the window is given as

$$\hat{f}(x, y) = \text{median}\{g(s,t)\} \tag{1.6}$$

where g(s,t) is the function defined over the window (s,t)

The min and max filter also works similar to median filter but they replaces min and max pixel values respectively present in the window rather than the middle pixel values. The min filter is defined as

$$\hat{f}(x, y) = \min\{g(s,t)\} \tag{1.7}$$

The max filter is given as

$$\hat{f}(x, y) = \max\{g(s,t)\} \tag{1.8}$$

The noise removed in the image can't be effectively visualized and histogram parameters show the effectiveness of noise removal. The performance of these filters was evaluated based on the standard deviation and mean values that were calculated from the histogram of MR images before and after filter was applied. The standard deviation and mean values should be low for the filtered image when compared to the noisy image. Based on this, the median filter was considered as the best to remove the noise. The drawback is that these filters will not be effective when the patterns of noise are adaptive. The PSNR value can be calculated using the below formula,

$$PSNR = 10\log_{10}\left[\frac{\sum\limits_{i}\sum\limits_{j} 255^2}{\sum\limits_{i}\sum\limits_{j}\left(X_{i,j} - \hat{X}_{i,j}\right)^2}\right] \tag{1.9}$$

where $X_{i,j}$ denotes the original image pixel

$\hat{X}_{i,j}$ denotes the restored image pixel

Signal to Noise Ratio specifies how much the noise is removed and is given as

$$SNR = 10\log_{10}\left[\frac{\sum_i\sum_j X_{i,j}^{2}}{\sum_i\sum_j\left(X_{i,j}-\hat{X}_{i,j}\right)^2}\right] \quad (1.10)$$

Tamilselvan et al. (2013) proposed the wavelet transform and curvelet transform for the denoising of medical images based on histogram equalization [4]. Wavelet technique uses the appropriate threshold value for the process of noise reduction. Histogram equalization uses the equalizing point function which stress/compress an image so that pixel values occur frequently get stretched more. In wavelet transform, the degraded signal is denoted by N and the observation is given as

$$Y=X+N \quad (1.11)$$

where X is the true signal
The true signal is estimated as

$$X = \sum_{i=0}^{N-1} \sigma_i\left(\left\langle X, g_i\right\rangle\right) g_i \quad (1.12)$$

where σ_i is the standard deviation defined over i

Curvlet technique preserves edges and singularities more effectively. The complexion of these techniques lies in the selection of threshold value. If the threshold value is too small, it cannot effectively remove the noise present in the image and if the value is too large, it removes the useful signal components. The threshold operator for de-noising are: Hard thresholding, Soft thresholding, affine thresholding. The histogram parameters like standard deviation, median and mode values are evaluated and the hybrid of both these techniques is best suited to remove noise. The drawback of this paper is that even though various threshold operators are used, the choice of global threshold which is constant didn't remove noise effectively.

B. Segmentation

Segmentation subdivides an image into different regions or objects based on the information found about objects in imaging data. The purpose of image segmentation is to partition into meaningful regions with respect to the application. Segmentation algorithms are based on one of two basic properties of intensity values discontinuity and similarity[20]. First category is to partition an image based on abrupt changes in intensity, such as edges in an image. Second category is based on partitioning an image into regions that are similar according to predefined criteria.

Yong yang et al. (2007), proposed the fuzzy c-means clustering algorithm for the image segmentation [21]. Fuzzy C-means algorithm is widely allows pixels to belong to multiple classes with varying degrees of membership. But the major operational complaint is that the FCM technique is time consuming. Fuzzy C-Means (FCM) is a method of clustering which allows one pixel to belong to two or more clusters. The FCM algorithm attempts to partition a finite collection of pixels into a collection of "C" fuzzy clusters with respect to some given criterion [6].
The cost function is defined as,

$$J = \sum_{j=1}^{N}\sum_{i=1}^{c} u_{ij}^{m} \|x_j - v_i\| \,\hat{}\, 2 \quad (1.13)$$

where u_{ij} - membership of data xj belongs to cluster i
m - fuzzification co-efficient
v - cluster center

The membership of the data is defined by,

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\|x_j - v_i\|}{\|x_j - v_k\|}\right)^{2/(m-1)}} \quad (1.14)$$

The cluster centers are updated using,

$$v_i = \frac{\sum_{j=1}^{N} u_{ij}^{m} x_j}{\sum_{j=1}^{N} u_{ij}^{m}} \quad (1.15)$$

Depending on the data, the classes can be identified using the similarity of pixels. The drawback of this technique is that it doesn't consider the spatial information of image into account and leads to misclassification and also the equation of calculating the membership is not effective. They have used the penalty term to overcome this shortcoming. This penalty term is inspired by normalized expectation algorithm and the Penalized FCM (PFCM) showed good result during segmentation when compared with FCM but didn't include the spatial information for segmentation.

Anam Mustaqeem et al. (2012) proposed the efficient algorithm for segmentation of brain tumor using watershed technique [5]. Watershed based segmentation group pixels of image based on their intensities. Watershed is the morphological tool. The two main steps in this technique are: the local minima of image gradient are chosen as the marker, then the regions are merged using this marker. The marker positions are either defined manually or with the help of mathematical morphological tools. The morphological tools are used to separate tumor region from the brain images. The various morphological tools are dilation, erosion, filling and expanding. They experimented this technique with the image size of 255x255. The shortcomings of this technique are that this will lead to over segmentation or under segmentation.

Evelin suji et al. (2013) proposed the adaptive thresholding technique to segment the pathological tissues like tumor from the healthy tissues. This technique is used when the images are captured under unknown lightning conditions [2]. It segments the lighter foreground from its background when the background level is not constant. Here they selected threshold value based on histogram. The histogram peaks will not be sharp if they are degraded by noise. This introduced error in selecting the threshold value. The key issues were how to subdivide the image and how to estimate threshold for each resulting sub image since threshold used for each pixel depends on location of pixel in terms of sub image. And also this technique is sensitive intensity in homogeneities.

Shilpa kamdi et al. (2013) proposed the region growing algorithm for the segmentation process [1]. In region growing, the neighboring pixels are examined and added to a region class if no edges are detected. This process is iterated for each boundary pixel in the region. If adjacent regions are found, region-merging algorithm is used in which weak edges are dissolved and strong edges are left intact. The first step in region growing is to select a set of seed points. Seed point selection is based on some user criterion like pixels in a certain gray-level range, pixels evenly spaced on a grid. The initial region begins as the exact location of these seeds.

The regions are then grown from these seed points to adjacent points depending on a region membership criterion. The criterion could be pixel intensity, gray level texture, or color. Since the regions are grown on the basis of the criterion, the image information itself is important. Then they concluded several important issues about region growing and they are: The suitable selection of seed points is important, noise or variation intensities may cause holes which lead to over segmentation. Dissimilar starting point may not result growing into identical regions. They concluded that segmentation is effective only if it includes the global information analysis and neither of these proposed algorithms work well by considering the correlation.

C. Feature Extraction

When the input to data algorithm is too large to be processed and it is suspected to be redundant, then the input data will be transformed into a reduced representation set of features (also named features vector). Transforming the input data into the set of features is called feature extraction. The need for the feature extraction is that if the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input. Features such as shape, texture, color, etc. are used to describe the content of the image.

Ryszard(2007) suggested the feature extraction techniques from images which are applicable in biometrics and the content based retrieval systems. The features are pixel-level features, local features and global features. Pixel-level features are calculated at each pixel such as color and location. Local features are calculated over the subdivision of image. Global features are estimated over the entire image. The color feature can be extracted based on the RGB color space. For image retrieval, histogram of query image is then matched against histogram of all images in the database using some similarity metric. Texture is one of the important features to recognize as well as classify the objects. Texture representation can be of two types: structural and statistical. Statistical features can be extracted by co-occurrence matrices, principal component analysis. The features like energy, entropy, correlation, inertia are extracted using co-occurrence matrix. Contrast is the measure of the local variation in the gray level co-occurrence matrix.

Contrast can be calculated from glcm as follows,

$$Contrast = \sum_{n=0}^{G-1} n^2 \left\{ \sum_{i=1}^{G} \sum_{j=1}^{G} P(i,j) \right\} \quad (1.16)$$

where G is the gray level

P(i,j) is the probability function defined over (i,j)

Entropy is given as

$$Entropy = -\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} P(i,j) \times \log\left(P(i,j)\right) \quad (1.17)$$

Correlation is defined as the measure the degree of correlation a pixel has to its neighbor over the whole image.

Correlation is specified as

$$Correlation = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \frac{\{i \times j\} \times P(i,j) - \{\mu_x \times \mu_y\}}{\sigma_x \times \sigma_y} \quad (1.18)$$

where μ_x is the mean defined over x

σ_x is the standard deviation over x

Shape descriptors are features calculated from object contours. The features are circularity, aspect ratio, sharpness, directedness and length irregularity. These features are then normalized before fed into the classifier for classification.

Inertia is specified as

$$Inertia = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \{i-j\}^2 \times P(i,j) \quad (1.16)$$

Shaheen ahmed et al. (2011) intensity, fractal texture, and level-set shape in segmentation of posterior-fossa (PF) tumor for pediatric patients [12]. First they carried out intensity normalization as the pre-processing step. Tumor segmentation is carried out using graph-cut. They have suggested the Kullback-Leibler divergence measure for feature selection. Intensity alone is not the sufficient feature for classification. Texture features are extracted using multifractional Brownian motion (mBm). The empirical estimate is given as

$$E\left\{|W_X(t,a)|^q\right\} = \frac{1}{N}\sum_{i=0}^{N-1} |W_X(t_i,a)|^q \qquad (1.19)$$

Intensity, FD, and mBm wavelet fractal texture features are extracted for tumor segmentation. Feature selection, on the other hand, is a technique for selecting a subset of relevant features for building robust learning models. Kullback–Leibler divergence (KLD) is one such feature selection technique between two-class conditional density functions approximated by finite mixture of parameterized densities. By using the entropy gain of features, KLD provides feature ranking. The limitation is that these features alone are not sufficient for efficient segmentation and the time complexity is also high.

D. Classification

Classification is the process to assign class label to the data based on the nature of data present in the trained dataset. Classification can be of two types: Supervised classification in which classes may be specified priori by an analyst and unsupervised classification which is the automatic clustering process. Classification involves two phases: training phase and testing phase [7]. In training phase, characteristic properties of images features are isolated based on this, unique description of each classification category i.e. training class is generated. In testing phase, these features are used to classify image features [8].

Sandeep et al. (2006) developed the neural network and support vector machine classifiers for the classification of brain images. Features extracted using wavelets are fed as inputs to the neural network classifier. Discrete Wavelet Transform uses the discrete set of wavelets to implement the wavelet transform. SVM [22] is the binary classification method that takes input from two classes and produces the output as the model file for the classification of data into the corresponding classes. Neural network [17][19] is the non-linear computational unit through which large class of patterns can be recognized. The performances of both these classifiers are evaluated and based on this neural network is found to be the efficient classifier.

Arthi et al.(2009) [18], proposed the hybrid of neural network and fuzzy technique for the diagnosis of hyperactive disorder. A combination of self organizing maps which is unsupervised technique and radial basis function which is supervised algorithm. In Self Organizing Map, learning process is carried out and learning parameter rate starts to decrease during the convergence phase. Radial Basis Function neural network [16] is a supervised technique for the non-linear data and in this no hidden layer units are present. Based on the degree of sensitivity to inputs, the hidden units in neural network are assigned with equal weights. They concluded that hybridization of these methods involves complexity and relaxation of training dataset is not possible in such scenarios. The comparative study of the various surveyed paper including the techniques involved and the problem identified are shown in table 1.

TABLE 1

Comparison table for various survey techniques

Author	Summary	Proposed Technique	Problems Identified
Yen-Jen Oyaiig et al. (2002)	Classification	Radial Basis Function Network	Non-stationary inputs
Faruquzzaman et al. (2006)	Image Segmentation	Split and Merge	Sensitive to the variation of the threshold value and it has the inability to adapt to the image semantics.
Sandeep et al. (2006)	Classification of brain images	Neural network and support vector machine	Ranges which are dynamic are not considered in training set calculations.
Yong yang et al. (2007)	Segmentation of brain tumors	FCM	Spatial information of the images are not considered while segmentation is performed.
Ryszard (2007)	Feature extraction	Co-occurrence matrix	Texture features are difficult to extract.
Arthi et al.(2009)	Classification of	Hybrid of neural network	Hybridization of these methods involves complexity and relaxation of training

	disorders	and fuzzy algorithm	dataset is not possible
Satpathy et al. (2010)	Pre-processing of images	MDB approach	Fails to provide sufficient smoothing
Wei Xu et al. (2010)	CT scan images pre-processing	Bilateral and Non-Local Means Filter	Number of iterations is more leads to time complexity
Salem Saleh Al-amri et al. (2010)	Segmentation of images	Thresholding	Selection of appropriate threshold value is tedious
Shaheen ahmed et al. (2011)	Feature extraction for posterior-fossa tumor identification	multifractional Brownian motion (mBm)	Time complexity is high
Bhausaheb Shinde et al. (2012)	Filters for pre-processing	Comparative study	These filters will not be effective when the patterns of noise are adaptive
Ajala Funmilola et al. (2012)	Segmentation of medical images	Fuzzy K-C-Means	Iterations to perform segmentation is more
Anam Mustaqeem et al. (2012)	Segmentation of brain tumor	Watershed	Leads to over-segmentation or under-segmentation
Tamilselvan et al. (2013)	De-noising of medical images	Wavelet and Curvlet transform	Choice of global threshold value is not constant
Evelin suji et al. (2013)	Segmentation of tumor	Adaptive threshold	Assignment of threshold value for sub-images are difficult
Shilpa kamdi et al. (2013)	Image Segmentation	Region growing	Dissimilar starting point may not result growing into identical regions.
Dhanalakshmi et al.(2013)	Segmentation of images	K-Means clustering	Clusters are not often spatially coherent and this is sensitive to initial outliers.
Atiq Islam et al. (2013)	Feature extraction	Multi-fractal technique	Fractal leads to infinite nesting of features

IV. Conclusions

After surveying through various pre-processing techniques for medical images, the filters should not blur the edges and it should provide sufficient smoothing. This criterion is satisfied by non-linear filter. Segmentation of tumor region is effective only if it includes the spatial information of the pixels present in the image since these pixels are highly correlated. Statistical features are the best for the classification in scenarios for medical images. Feature Extraction using Co-occurrence matrices are suited for statistical features since they deal with the pixel co-occurrences. Classification of tumor region is optimal when it is done by neural network classifier.

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