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SVM Based Classification of Soft Tissues in Brain CT Images Using Wavelet Based Dominant Gray Level Run Length Texture Features

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Abstract: Soft tissues classification and segmentation from brain computed tomography image data is an important but time consuming task performed manually by medical experts. Automating this process is challenging due to the high diversity in appearance of tumor tissue among different patients and in many cases, similarity between tumor and normal tissue. The objective of this work is to classify and segment the brain soft tissues from computed tomography images using the wavelet based dominant gray level run length feature extraction method with Support Vector machine (SVM) classifier. A dominant gray level run length texture feature set is derived from the high frequency sub bands of the image to be decomposed using 2 level discrete wavelet transform. Multilevel dominant eigenvector estimation algorithm and the Bhattacharyya distance measure can be used to reduce the dimension of the feature vector and the high degree of correlation between neighborhood features. The selected optimal run length texture features are fed to the SVM to classify and segment the brain soft tissues. The method is applied on real data of 120 computed tomography normal and abnormal tumor images. The results are compared with the radiologist labeled ground truth. Quantitative analysis between ground truth and the segmented soft tissues and tumor is presented in terms of classification accuracy. From the analysis and performance measures like classification accuracy, it is inferred that the brain soft tissues classification is best done using the SVM with the wavelet based dominant run length feature extraction method. An average accuracy rate of above 98% was obtained using this classification and segmentation algorithm.

Key words: Dominant Gray Level Run Length Matrix method (DGLRLM) · Support Vector Machine classifier (SVM) · Computed Tomography (CT) · Multilevel Dominant Eigenvector Estimation algorithm (MDEE) · Bhattacharyya Distance Measure (BDM)

INTRODUCTION

In recent years, medical CT Images have been applied in clinical diagnosis widely. That can assist physicians to detect and locate pathological changes with more accuracy. CT images can be distinguished for different tissues according to their different gray levels. The images, if processed appropriately can offer a wealth of information which is significant to assist doctors in medical diagnosis. A lot of research efforts have been directed towards the field of medical image analysis with the aim to assist in diagnosis and clinical studies [1]. Pathologies are clearly identified using automated CAD system [2]. It also helps the radiologist in analyzing the digital images to bring out the possible outcomes of the diseases. The medical images are obtained from different imaging systems such as MRI scan, CT scan and Ultra sound B scan. The CT has been found to be the most reliable method for early detection of tumors because this modality is the mostly used in radio therapy planning for two main reasons. The first reason is that scanner images contain anatomical information which offers the possibility to plan the direction and the entry points of radio therapy rays which have to target only the tumor

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region and to avoid other organs. The second reason is that CT scan images are obtained using rays, which is same principle as radio therapy. This is very important because the intensity of radio therapy rays have been computed from the scanned image. Advantages of using CT include good detection of calcification, hemorrhage and bony detail plus lower cost, short imaging times and widespread availability. The situations include the patient who are too large for MRI scanner, claustrophobic patients, patients with metallic or electrical implant and patients unable to remain motionless for the duration of the examination due to age, pain or medical condition. For these reasons, this study aims to explore the methods for classifying and segmenting soft tissues in brain CT images. Image segmentation is the procss of partitioning a digital image into set of pixels. Accurate, fast and reproducible image segmentation techniques are required in various applications. The results of the segmentation are significant for classification and analysis purposes. The limitations for CT scanning of head images are due to partial volume effects which affect the edges produce low brain tissue contrast and yield different objects within the same range of intensity. All these limitations have made the segmentation more difficult. Therefore, the challenges for automatic segmentation of the CT brain images have many different approaches. The segmentation techniques proposed by Nathali Richarda et al and Zhang *et al.* [3, 4] include statistical pattern recognition techniques. Kaiping *et al.* [5] introduced the effective particle swarm optimization algorithm to segment the brain images into Cerebro spinal fluid (CSF) and suspicious abnormal regions but without the annotation of the abnormal regions. Dubravko et al and Matesin *et al*. [6, 7] proposed the rule based approach to label the abnormal regions such as calcification, hemorrhage and stroke lesion. Ruthmann *et al.* [8] proposed to segment cerebro spinal fluid from computed tomography images using local thresholding technique based on the maximum entropy principle. Luncaric et al proposed [9] to segment CT images into background, skull, brain, ICH, calcifications by using a combination of k means clustering and neural networks. Tong et al proposed [10] to segment CT images into CSF, brain matter and detection of abnormal regions using unsupervised clustering of two stages. Clark *et al.* [11] proposed to segment the brain tumor automatically using knowledge based techniques. From the above literature survey shows that intensity based statistical features are the most straight forward and have been widely used, but due to the complexity of the pathology in human brain and the high quality required by clinical diagnosis, only intensity features cannot achieve acceptable result. I such applications, segmentation based on textural feature methods gives more reliable results. Therefore texture based analysis have been presented for classification and segmentation of soft tissues such as wavelet based dominant gray level run length matrix feature extraction method is used and achieve the promising results.

MATERIALS AND METHODS

Most classification techniques offer gray level (i.e) pixel based statistical features. The proposed system is divided into 3 phases i) Discrete wavelet decomposition (ii) Feature extraction and selection (v) Classification and Evaluation. For the feature extraction, we discovered the method wavelet based dominant gray level run length feature extraction method, then for the feature selection, we use MDEE algorithm and BDM to reduce the dimension of the feature vector and the high degree of correlation between neighborhood features. The selected optimal run length texture features are fed into the SVM classifier to classify and segment the soft tissues in brain CT images.

Discrete Wavelet Decomposition: Daubechies wavelet filter of order two is used and found to yield good results in classification of the brain soft tissues in CT images. A two level wavelet decomposition of region of interest is performed which results in four sub bands. In 2D wavelet decomposition [12], the image is represented by one approximation and three detail images representing the low and high frequency contents image respectively. The approximation can be further to produce one approximation and three detail images at the next level of decomposition, wavelet decomposition process is shown in Figure 1. A1 and A2 represent the wavelet approximations at 1^{st} and 2^{nd} level respectively and are low frequency part of the images. H1, V1, D1, H2, V2, D2 represent the details of horizontal, vertical and diagonal directions at 1^{st} and 2^{nd} level respectively and are high frequency part of the images. The high frequency sub bands, that represents the most clearest appearance of the changes between the different textures. The dominant run length texture features extracted from 2^{nd} level of these high frequency sub bands are useful for this classification and segmentation algorithm.

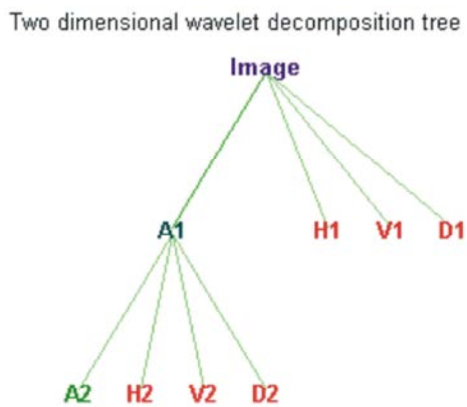

Fig. 1: Two level discrete wavelet decomposition

Feature Extraction and Feature Selection: Texture analysis is a quantitative method that can be used to quantify and detect the structural abnormalities in different tissues. As the tissues present in brain are difficult to classify using the shape or the intensity level of information, the texture feature extraction is founded to be very important for further classification. The purpose of the feature extraction is to reduce the original data set by measuring certain features that distinguish one region of interest from the another. The analysis and characterization of textures present in the medical images can be done by wavelet based dominant gray level run length feature extraction method.

Algorithm for feature extraction is as follows:

- Obtain the sub-image blocks, starting from the top left corner.
- Decompose sub-image blocks using 2 level 2-D DWT.
- Derive the gray level run length matrix (GLRLM) [13] for two level high frequency sub bands of the discrete wavelet decomposed image with 1 for distance and 0,45,90 and 135 degrees for è and averaged.
- From these gray level run length matrices, the following dominant run length texture features called wavelet dominant run length texture features (WDRLT) [14] are extracted.

Then the feature values are normalized by subtracting minimum value and dividing by maximum value minus minimum value. Maximum and minimum values are calculated based on the training data set. In the data set, if the feature value is less than the minimum value, it is set to minimum value. If the feature value is greater than the maximum value, it is set to maximum value. Normalized feature values are then optimized by the MDEE [15] algorithm and the BDM [16]. The optimized features obtained from MDEE algorithm and BDM are Long Run Low Gray Level emphasis (LRLGE), Long Run High Gray level emphasis (LRLGE). The long run high gray level emphasis captures the inhomogeneous nature of the texture features and long run low gray level emphasis captures the homogeneous nature of the texture features.

Table 1: Features extracted using DGLRLM method

SI-no	High order WDRLT features
1.	Short Run Low Gray Level emphasis (SRLGE)
2.	Short Run High Gray Level emphasis (SRHGE)
3.	Long Run Low Gray Level emphasis (LRLGE)
4.	Long Run High Gray level emphasis (LRLGE)

Classifier: Classification is the process where a given test sample is assigned a class on the basis of knowledge gained by the classifier during training. To make the classification results comparable and for exhaustive data analysis, we have used leave one out classification method for the SVM classifier.

Support Vector Machine Classifier: Support vector machine [17] performs the robust non-linear classification with kernel trick. SVM is independent of the dimensionality of the feature space and that the results obtained are very accurate. it outperforms other classifiers even with small numbers of available training samples. SVM is a supervised learning method and is used for one class and n class classification problems. it combines linear algorithms with linear or non-linear kernel functions that make it a powerful tool in the machine learning community with applications such as data mining and medical imaging applications. To apply SVM into non linear data distributions, the data can be implicitly transformed to a high dimensional feature space where a separation might become possible. For a binary classification given a set of separable data set with n samples $x = \{x_i\}$, $i = 1, 2 \ldots n$, labeled as $y_i = \pm 1$. it may be difficult to separate these 2 classes in the input space directly. Thus they are mapped into a higher dimensional feature space by $x' = f(x)$.

The decision function can be expressed as

$$f(x) = w.x + \rho \tag{1}$$

where w.x + p = 0 is a set of hyper planes to separate the two classes in the new feature space. Therefore for all the correctly classified data,

$$y_i f(x) = y_i (w.x + \rho) > 0, i = 1, 2 ..... n \quad (2)$$

by scaling w and ρ properly, we can have f(x) = w.x+ρ = 1 for those data labeled as +1 closes to the optimal hyper plane and f(x) = w.x + ρ = -1 for all the data labeled as -1 closes to the optimal hype r plane. In order to maximize the margin the following problem needs to be solved.

$$\min (\|w\|^2/2)$$

$$\text{subject to } y_i f(x) = y_i (w.x + \rho) \geq 1, i = 1, 2 .. n \quad (3)$$

It is a quadratic programming problem to maximize the margins which can be solved by sequential minimization optimization. After optimization, the optimal separating hyper plane can be expressed as

$$f(x) = \sum_{i=1}^{N} \alpha_i Y_i K(x_i, x) + \rho \quad (4)$$

where k(.) is a kernel function, ñ is a bias, α is the solutions of the quadratic programming problem to find maximum margin. when α is non zero, are called support vectors, which are either on or near separating hyper plane. the decision boundary (i.e.) the separating hyper plane whose decision values f(x) approach zero, compared with the support vectors, the decision values of positive samples have larger positive values and those of negative samples have larger negative values. Therefore the magnitude of the decision value can also be regarded as the confidence of the classifier. The larger the magnitude of f(x), the more confidence of the classification by choosing a Gaussian kernel function:

$$k(x,y) = e^{-\gamma} \|x-y\|^2 \quad (5)$$

where the value of ã was chosen to be 1 and has good performance for the following two reasons. first reason is the Gaussian model has only one parameter and it is easy to construct the Gaussian SVM classifier compared to polynomial model which has multiple parameters. Second reason is there is less limitation in using Gaussian kernel function due to nonlinear mapping in higher dimensional space.

RESULTS AND DISCUSSIONS

This section describes the classification performance of the SVM classifier used for the classification and segmentation of soft tissues in brain CT images with wavelet based dominant gray level run length texture features. The results from the SVM classifier is evaluated using statistical analysis. An experiment has been conducted on a real CT scan brain images and the 120 images were partitioned arbitrarily into training set, testing set with equal number of images. The accuracy of the SVM classifier is evaluated based on the error rate. This error rate can be described by the terms true and false positive and true and false negative as follows.

True Positive (TP): Abnormal cases correctly classified,

True Negative (TN): Normal cases correctly classified,

False Positive (FP): Normal cases classified abnormal,

False Negative (FN): Abnormal cases classified normal.

The above terms are used to describe the clinical efficiency of the classification and segmentation algorithm.

Sensitivity = TP / (TP + FN) * 100 Specificity = TN / (TN + FP) * 100
Accuracy = (TP + TN) / (TP + TN + FP + FN) * 100.

Accuracy is the proportion of correctly diagnosed cases from the total number of cases. Sensitivity measures the ability of the method to identify abnormal cases. Specificity measures the ability of the method to identify normal cases. To make the classification results comparable and for exhaustive data analysis, leave one out cross validation method can be used to estimate the classifier performance in unbiased manner. In this method, in each step one data set is left out and the classifier is trained using the rest and the classifier is applied to the left out data set. This procedure is repeated such that each data set is left out once. In our application for evaluating the classification accuracy, 10 fold cross validation method is done on the data set collected from 120 images. (60 normal and 60 abnormal). The images are divided into 10 sets each consisting of 6 normal images and 6 abnormal images. Then 9 sets are used for training

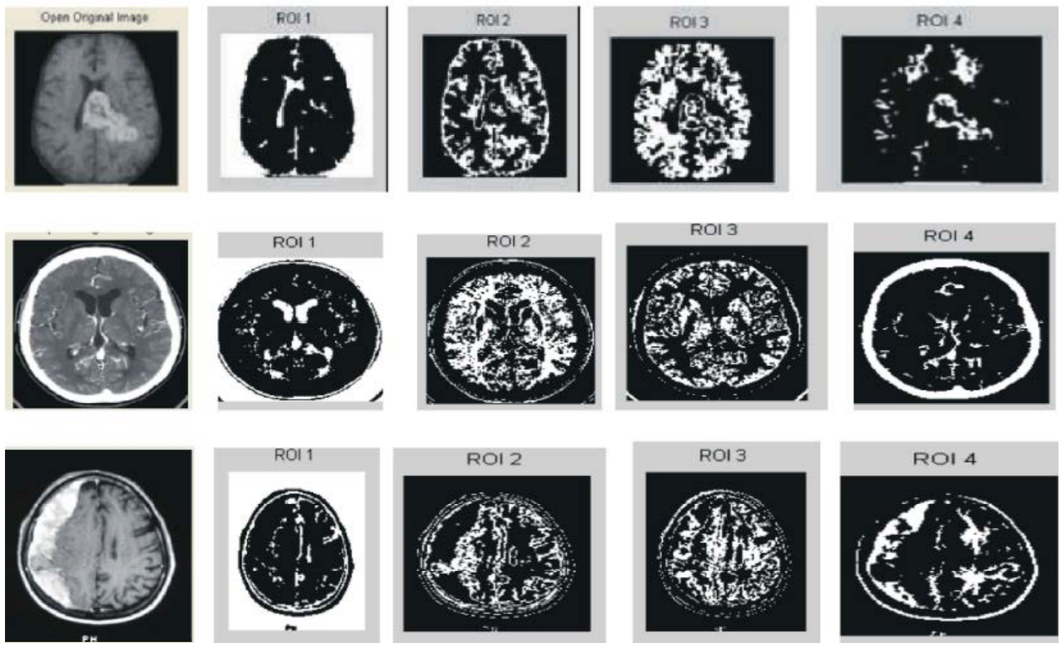

Fig. 2: Segmented results for sample images

Table 2: Classification performances of the SVM classifier for 120 images

Classification parameters	SVM classifier
TP	60
TN	58
FP	2
FN	0
Sensitivity in %	100%
Specificity in %	96.6%
Classification accuracy in %	98.3%

and remaining set is used for testing. In next iteration (2-10), 9 sets are used for training and remaining set is used for testing. This process is repeated for 10 times. The classification accuracy was calculated for by taking the average of all the correct classifications of 10 iterations.

Figure 2 shows the input CT brain images and the corresponding segmented Region of interests (ROI). The ROI1 represents gray matter (GM), the ROI2 represents the white matter (WM), the ROI3 represents the cerebro spinal fluid(CSF) and the ROI4 represents the abnormal tumor region.

Table 2 shows the classification performances of the SVM classifier using wavelet based dominant run length feature extraction method. The results show that, if the representative samples increased, it gives good classification accuracy for the 10 fold cross validation method.

CONCLUSION

In this work a new wavelet based dominant run length feature extraction method is proposed for the classification and segmentation of soft tissues in the brain CT images using the SVM classifier is proposed. The algorithm has been designed based on the concept of different types of brain soft tissues (CSF, WM, GM, Abnormal tumor region) have different textural features. The results show that the new wavelet based dominant run length feature extraction method yields better results based on the SVM classifier. It is found that this method gives favorable result with accuracy percentage of above 98% for the CT images that are being considered. This would be highly useful as a diagnostic tool for radiologists in the automated classification and segmentation of brain CT images.

The goal of this work is to classify and segment the soft tissues in brain CT images using new wavelet based dominant gray level run length feature extraction method. Hence it is concluded that the SVM supported by this texture analysis method can be effectively used for classification and segmentation of brain soft tissues in CT images. Use of large data bases is expected to improve the system robustness and ensure the repeatability of the resulted performance. The automation procedure proposed in this work using SVM enables proper abnormal tumor region detection and segmentation thereby saving time and reducing the complexity involved.

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