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Medical CT Image Classification

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1. Introduction

With the rapid development of CT imaging technology, CT images that include various human body part like stomach, head, face, back,chest and pelvis are obtained in order to help doctors diagnose some illness like brain tumor, lung cancer, and so on. However, the efficient usage of these large amounts of image data is limited by the current image processng level and also by doctor's experience, knowledge and some other subjective factors like whether the doctor is tired or not. Thus proper imaging, segmenting, transferring, classificaton and processing of the image by computer software is necessary.

How to process all the available image data and make computer aided diagonosis system(CAD) be a reality is one of the hotspots in recent research. Recently there are some researches that focus on this specific field. **Yoshida** et al.(2004), proposed a lung disease detection method based on Generic Algorithms(GA) and template matching. **El-bazl** et al.**(2003)**, proposed a novel CAD system based on the symmetrical feature of lung and also based on that tumors appear to be round . These methods are effective for some specific patients. However, sometimes the oversimplified algorithm can not get ideal results becasue of the heterogeneity of human body.

This chapter introduces a scheme that uses NCut(Normalized Cut) image segmenter, novel edge features and SVM(Support Vector Machine) classifier to implement CT image classfication and brain tumor detection. Using real data, the propsoed algorithm was tested and some basic conclusions were given out.

2. Integration of NCut segmentation and SVM classifier

Shi J,Malik J(2000) proposed Normalized Cut(Ncut) as a good image segmentation method and soon NCut drew great attention in recent years because it maximizes the similarity of the same group and the dissimilarity of different groups simutaneously. Support vector machine(SVM) is proposed by V. Vapnik in 1963. And it is a promising statistical learning technique for machine learning. Therefore the problem of regression or time series analysis and pattern recognition like classification and decision can be solved by SVM. The medical diagnosis problem is a problem of pattern recognization and then in essence it is a classification problem. Of course, Ncut can not be followed by SVM classifiier directly since the output of Ncut is seveval subimages obtained from NCut segmenting while the input of SVM classifier is a high-dimensional feature vector. So to match the above 2 tools we need find an effective and efficient way to extract and then select the features.

For feature extraction, we get the multi-resolution edge by wavelet transformation and then compute the mean and variance of the edge matrix as a novel feature component besides traditional grey and texture features.

Here some more detail information should be given out to make our newly proposed algorithm more clearly and implementable. As shown in Figure 1 and Figure 2, the training and classification system shared one common interface, i.e. the same interface can be used as either training or classifying aims. The main difference lies in that for training procedure, Ncut segmentation is performed based on some prior information about the medical structure of the human body part (e.g. For brain tumor CAD system, we set the number of partition be about 10). Then for a given sample image, we get the best number by try some very close partition number. Since for the training sample images, the tumor's relatively precise information is known. So then we can extract the corresponding subimages and exact the features and then train the SVM classfier using different kernal functions or some kind of combination of the different kernals(see also Figure2 for intuitive description).

For the diagonosis system, we use scheme shown in Figure1. Here we load the trained classifier implicitly. Because the well-trained classifier can be used as a reference and it is very helpful for the CAD system to work well.

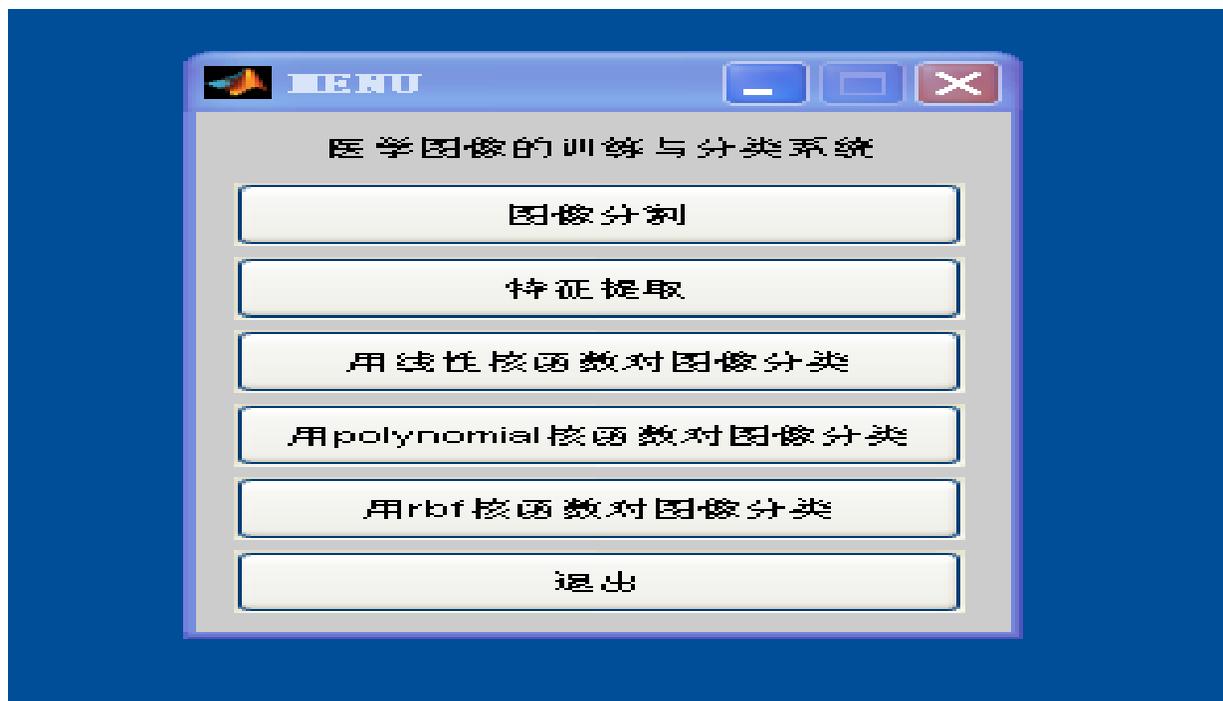The main interface of the proposed computer aided diagnosis (CAD) is as shown in Fig.1.

Fig. 1. Main interface of the software

The novel scheme can be briefly described as following: First,we perform image segmentation using NCut in order to get the ROI(Region of Interest). Meanwhile, this step is also helpful to reduce the data amount to be processed later. Then feature extraction using various selected math analysis tools was done for the ROI and the corresponding symmetric region and the feature spaces are constructed based on the extracted features. After that we trained the SVM classifier using selected samples and features. Finally,Computer Aided Diagnose (CAD) results can be get using the trained SVM classifier and real CT images.

Experiments with brain CT images shows that the new algorithm can make correct diagnose and thus help doctor to perform their work more efficiently.

Note that prior to the diagnosis phase, we need get some well-trained data for SVM classfier using some classical trainng dataset which is obtained from hospital and was well agreed by medical experts. Then we have some well-trained SVM classifier using linear, polynomial, radial basis function(RBF) various kernal function.

The expression of the polynomial, Gauss and Sigmoid kernal functions are as follows:

1. polynomial: $k(x,x_i) = [(x_i,x) + 1]^q$

2. Gauss: $K(x,x_i) = exp[-\sigma |x - x_i|^2]$

3. Sigmoid: $K(x,x_i) = tanh(\sigma(x \cdot x_i) + c)$

Here, for each kind of the kernal function, there is one or two key parameter. For polynomial, the order q, for

Gauss kernnal it's the variance-related parameter σ and for Sigmod kernal σ and c.
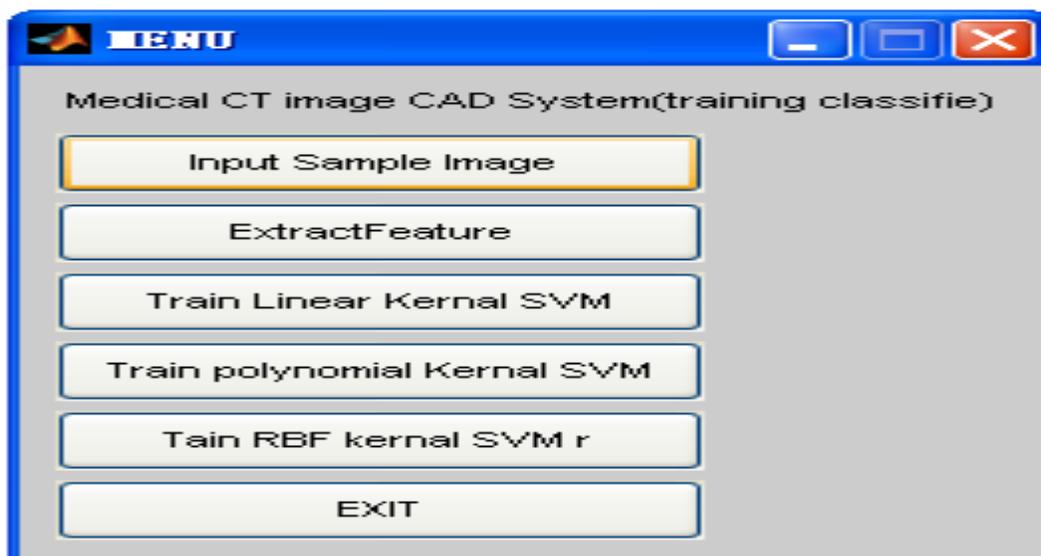

Fig. 2. Main interface of the training process

2.1 NCut-based image segmentation

Till now, researchers have proposed a lot of methods for image segmentation. These methods can be broadly classified into the following catergories: 1)Local filtering method ; 2) Active contour or snake; 3) Region growth ,split and merge algorithm like K-means, JSEG(J-value segmentation) and EM(Expectation Maximum); 4) Level set method that is based on the global minumum of energy function; 5) Mean shift method that is based on statistical iteration. The major drawback of the mentioned methods is that they fail to find global optima for the high-dimensional, nonliear problem and some of them can not guarantee the continuity since they use only the local information so they can not guarantee the continuity of the edge. NCut is proposed by J.Shi and J.Malik in 1997 to perform the task of image segmentation and image clustering. NCut has three major features: 1) It converts the problem of image segmentation into the one of graph partition; 2) It uses a global optimum criteria; 3) It maximizes the similarity of the same group and the dissimilarity of different group at the same time.

2.1.1 Math basis for NCut image segmentation

For a given input image or feature set, a weighted unidirectional graph is constructed first. In the graph, each pixel or feature point stands for one node in the graph. Then a global minimum normalized cut in the graph is searched for so as to divide the nodes in the graph. After all the nodes is partitioned, the image segmentation or feature set clustering is done.

The set of points in a feature space are represented as an arbitrary unidirectional graph $G = (V, E)$. Assume we divide the given graph $G = (V, E)$ into two independent disjoint parts A and B, i.e. $A \cap B = \Phi$ and $A \cup B = V$.

The partition can be done by simply removing the edges connecting the two parts. The dissimilarity of these two parts can be defined as the summation of all the weights that have been removed. It is called cut:

$$cut(\mathbf{A}, \mathbf{B}) = \sum_{i \in A, j \in B} w(i, j) \tag{1}$$

Where $w(i, j)$, the weight on each edge, is a function of similarity between node i and j.

The optimal bipartitioning of a graph is the one that minimize the cut value. However, minimum cut is not optimal cut because cut value is directly related to the number of edges in the cut. To evaluate the dis-similarity between different groups, we have the new measure called normalized cut(Ncut) as following:

$$Ncut(\mathbf{A}, \mathbf{B}) = \frac{cut(\mathbf{A}, \mathbf{B})}{assoc(\mathbf{A}, \mathbf{V})} + \frac{cut(\mathbf{A}, \mathbf{B})}{assoc(\mathbf{B}, \mathbf{V})} \tag{2}$$

Where $assoc(\mathbf{A}, \mathbf{V}) = \sum_{u \in A, v \in V} w(u, v)$ is the total conncetion from the nodes in A to all the nodes in the graph and $assoc(\mathbf{B}, \mathbf{V})$ has similar definition.

In the same spirit, we can define a measure for total normalized association within groups for a given partition as:

$$Nassoc(\mathbf{A}, \mathbf{B}) = \frac{assoc(\mathbf{A}, \mathbf{A})}{assoc(\mathbf{A}, \mathbf{V})} + \frac{assoc(\mathbf{B}, \mathbf{B})}{assoc(\mathbf{B}, \mathbf{V})} \tag{3}$$

Where $assoc(\mathbf{A}, \mathbf{A})$ and $assoc(\mathbf{B}, \mathbf{B})$ represent total weights of edges connecting nodes within A and B respectively.

Another important property is that $Ncut(\mathbf{A}, \mathbf{B})$ and $Nassoc(\mathbf{A}, B)$ is related by the following equation:

$$Ncut(\mathbf{A}, \mathbf{B}) = 2 - Nassoc(\mathbf{A}, \mathbf{B}) \tag{4}$$

Hence, the partition criteria minimize the disassociation between different groups and maximize the association between different groups are in fact identical and thus can be met simutaneously.

Although NCut is computational complex since it is actually an NP complete problem. An approximate discrete solution can be found using the algorithm desribed in the next part.

2.1.2 Implementation of image segmentation

Given a partition of nodes of a graph V into two sets A and B, let $\mathbf{x}$ be an indicator vector of size N ($N = |\mathbf{V}|$) and $x_i = 1$ stands for node i belongs to set A while $x_i = -1$ indicates that

node i is in set B. Let $d_i = \sum_j w(i,j)$ be the total connection from node i to all the other nodes. With these definitions for $\mathbf{x}$ and d, we can rewrite *Ncut* as:

$$Ncut(\mathbf{A}, \mathbf{B}) = \frac{cut(\mathbf{A}, \mathbf{B})}{assoc(\mathbf{A}, \mathbf{V})} + \frac{cut(\mathbf{A}, \mathbf{B})}{assoc(\mathbf{B}, \mathbf{V})}$$

$$= \frac{\sum_{x_i>0, x_j<0} -w_{ij} x_i x_j}{\sum_{x_i>0} d_i} + \frac{\sum_{x_i<0, x_j>0} -w_{ij} x_i x_j}{\sum_{x_i<0} d_i} \tag{5}$$

Let $\mathbf{W}$ be an $n \times n$ symetric matrix and with $\mathbf{W}(i,j) = w_{ij}$, and let $\mathbf{D}$ be a diagonal matrix with d_i on its diagnoal, i.e. $\mathbf{D} = diag(d_1, d_2, \cdots, d_N)$.

Denote $b = \dfrac{\sum_{x_i>0} d_i}{\sum_{x_i>0} d_i}$ and $y = (1+x) - b(1-x)$, where 1 be an Nx1 vector of all ones. Thus the global optimum problem can be simplified as(for detail derivation see ref[2]):

$$min_{\mathbf{x}} Ncut(\mathbf{x}) = min_{\mathbf{y}} \frac{\mathbf{y}^T (\mathbf{D} - \mathbf{W}) \mathbf{y}}{\mathbf{y}^T \mathbf{D} \mathbf{y}} \tag{6}$$

Subject to

$$y_i \in \left\{ 1, \frac{-\sum_{x_i>0} d_i}{\sum_{x_i<0} d_i} \right\}, \text{ and } \mathbf{y}^T D \cdot 1 = 0.$$

If y is relaxed to take on only real value, we can minimize Eq.(6) by solving the generalzed eigenvalue

$$(\mathbf{D} - \mathbf{W}) \mathbf{y} = \lambda \mathbf{D} \mathbf{y} \tag{7}$$

Eq.(7) can be rewrite as a standard eigenvalue system as below:

$$\mathbf{D}^{-\frac{1}{2}} (\mathbf{D} - \mathbf{W}) \mathbf{D}^{-\frac{1}{2}} \mathbf{z} = \lambda \mathbf{z} \tag{8}$$

where $\mathbf{z} = \mathbf{D}^{\frac{1}{2}} \mathbf{y}$.

The important result that we used here is that the second smallest eigenvector of the generalized eigensystem (7) is the real value solution to the normalized cut problem. Using the vector that corresponding to the second smallest eigenvalue, we can segment each image into two parts. Then an iterative method is used to segment every part of the image.

2.1.3 Segmentation results

Before NCut Image Segmentation and Support Vector Machine Classifier for Computer Aided Diagnosis, sometimes a brief pre-processing procedure should be done in order to classify one given CT image into its corresponding coarse class so that one can put the images under their proper folders. The software we developed using VC platform and the initial software interface is given out as in the following figure (Fig.3).
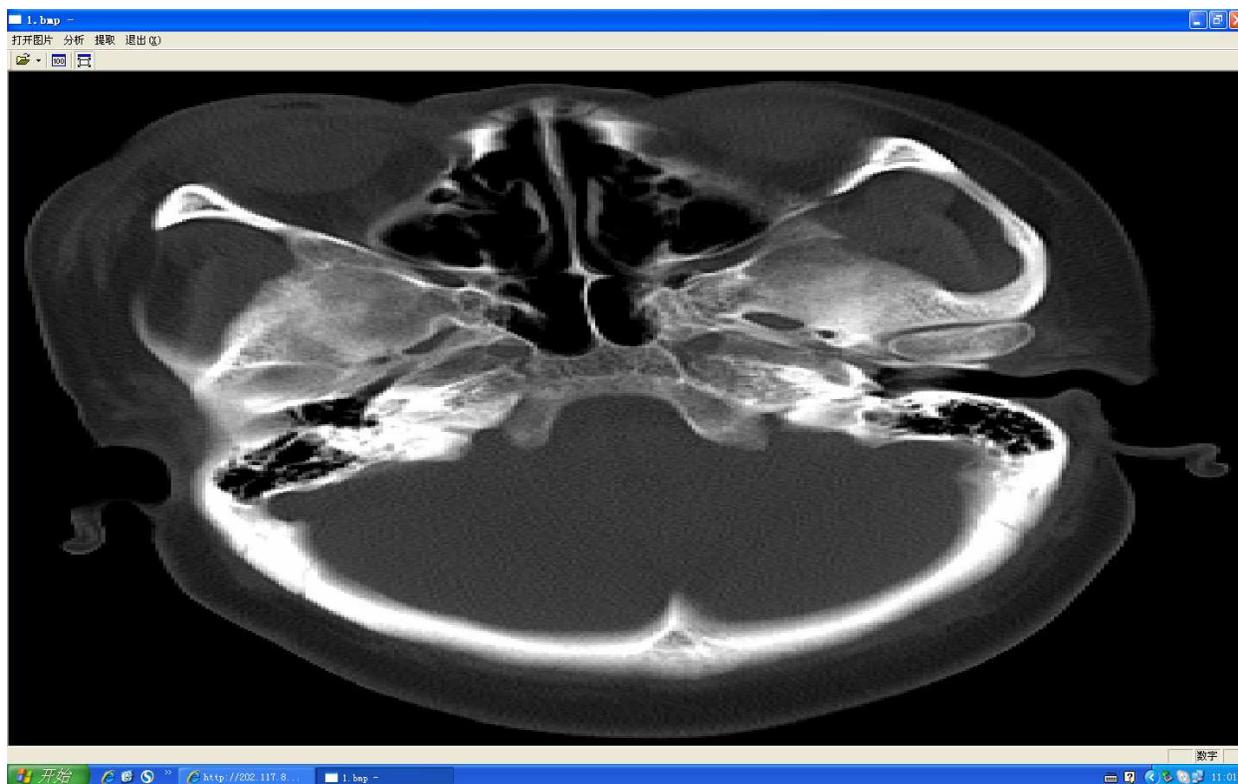
Fig. 3. Initial interface for coarse classification

Then, using the implementation procedure discussed above, we simulated the performance of image segmentation on the platform of Matlab7.0 software.

For a given CT brain image that is known to have a tumor somewhere, we perform the image segmentation task and annotate different regions using different colors. And the original and resultant images are shown in shown in Fig4 and Fig5 respectively. From Fig5, it can be seen that the image has been segmented into 10 parts and the edge of different parts is obvious. From Fig5, the possible tumor part has been annotated as blue part, and the shape and size of the corresponding part can be get by its coordinates and the distance between the edge points.
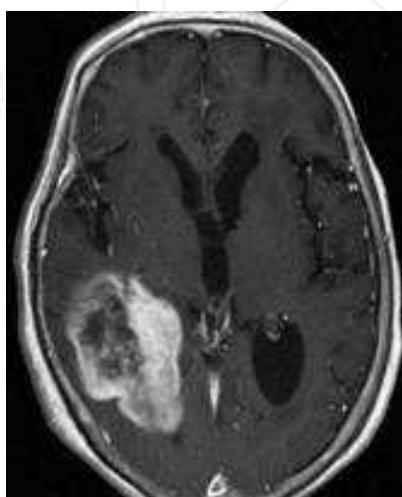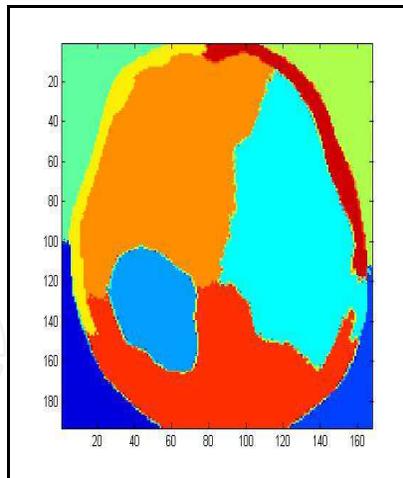

Fig. 4. Original brain CT image

Fig. 5. Image segmented

2.1.4 Feature components for SVM classifier

After the processing described in the former part,the region of brain tumor has been extracted. Next, we need distinguish tumor and normal tissue by machine learning method. To do this, it is significant to describe different tissues with proper features. Many useful image features like grey descriptors, geometry feature and texture characteristics has been proposed to do these. Athough this features has solid mathmetical foudation, they can not fully describe the featurs of medical CT image. Here we proposed to use multi-resolution edge feature as an additional feature and compute the mean and variance of the matrix of edge pixels as basic features. The motivation of our novel feature component is that the tumor image has high space resolution and it has rich edge, grey and texture information.To get the new edge feature components, we get the multi-resolution edge by wavelet transformation and searching maximum modulos first, and then compute the mean and variance of the edge matrix.

Combining traditional feature and the novel featurs proposed here, the features used in this part is summed up in Table1. altogether we use 22 dimensional features to train and test our SVM classifier.

Feature Class and dimension	Description of the feature component
Edge (2-D)	Mean of the edge matrix Variance of the edge matrix
Grey（4-D)	Mean of the grey value Variance of the grey value Bias of the grey value Peak value of the grey value
texture（16-D)	Energy Contrast Correlation Entropy

Table 1. Features used in the CAD system

2.1.5 Classification using the integrated NCut segmenting and SVM classifier

We focuse on how to label different part of images with different names and describe their corresponding size and location using lots of unknown brain CT images.

This part we proposed to use support vector machine (SVM) to classify the image under test. Support vector machine(SVM) is one kind of pattern recognition which is based on statistical learning theory and it is proposed by V. Vapnik in 1963[3].Its basic idea is to tranform a nonlinear dividing problem into a linear one by some kind of kernal function. The sample space will be mapped to a high dimensional or even infinite dimension feature space (also called Hibert space). Then an optimal hyperplane for classification or regression is found.

SVM has the following advantages:

1. It's designed to use limited samples to get optimum solution for practical problem;
2. It can ensure to find the global rather than local optimum solution.
3. The generalization ability of SVM is very good with relatively less computation complexity.

Therefore SVM has drawn increasing adoption in many fields. However, one major problem is that the computation is complex, the idea of kernal funciton sovles this difficluty. By proper selected kernal function, we can greatly reduce the time of training without lost of any precision.

The problem is a nonlinear classification one, therefore we use nonlinear SVM that uses kernel function $K(x_i,x)$. The kernel function can be polynomial, Gauss and Sigmoid functions.

First, we describe the dataset used and the illustration is given out in Table 3. Specifically, our test in mainly focusing on brain CT images to detect brain tumour.

For other body part's images, using coarse-to-fine classification for large amounts of the incoming CT images we can classify the input CT images to its corresponding class based on the imaging part. The algorithm can be described as following:

Step 1. Extract and select features like grey, edge and texture features. Note the features used here may be different from the ones that used in the CAD system presented in this chapter. Because for efficiency, the features used here is global instead of local. So we can use more statistical feature to represent one kind feature. E.g. we propose to use 5-D edge features (the length of the region, the area of the region, etc) to quantify the edge feature.

Step 2. Use Euclidean distance as the measurement for classification. The definition of Euclidean is d=sqrt($\sum$(xi1-xi2)^ 2)   i=1,2, ...n

The hardware platform for the simulation is as following: CPU is Intel Core Duo（1.6GHZ) and momery is 1024MB. The software platform is Windows XP as OS and Matlab7.0 code for Ncut-based image segmentation and LibSVM-2.86[5] for SVM training and testing. Some VC++6.0 codes are also developed for interoperating and interface.

For training procedure, the image used here is 512×512. First we selected 100 brain CT images as training samples and extracted 124 possible tumour images. And among the 124 sub-images, 68 images are positive samples and 56 images are negative images. And then the 22-D features for each sub-image are extracted according to Table1. After that, the extracted features are sent to SVM to train the SVM classifier.

In table 2, detail information about the data used is given out.

Image Type & features	Brian CT	Head CT
Data size	402MB	92.1MB
Data source	Provided by a hospital in Xi'an, , China	Provided by a hospital in Xianyang, Xi'an, China
Number of patients	37	10
Sex portion	20 males and 17 females	6 males and 4 females

Table 2. Descripton of the used data

Next, for testing procedure, we selected 50 brain CT images. Among which we detected 60 possible tumour regions. And 30 sub-images are positive samples while 30 are negative samples. And we set penalty parameter as 100,150 and 200 respectively. And the optimum parameter value can be get by comparing the value of classification precision. Note here the classification precision (P) is calculated as:

$$P=Nc/Nt \tag{9}$$

Where Nc and Nt stands for the number of correct classified samples and the number of total samples respectively.

Tumour identification and quantization is important for the future cure. So CAD brain tumor diagnosis has potential applications. The method presented in this paper gives a useful implementation of this CAD system. Furthermore the proposed Ncut-based image segmentation is also useful for other application like CBIR(Content-based Image Retrieval) system.

And from pririo knowledge, the region of tumor image can be get by simply click that region and then we can show it in Fig.5 or save it in a file so that the region can be used later as training sample in the following steps.

Penalty factor	P for Polynomial kernal	P for RBF kernal	P for Sigmoid kernal
C=100	93.3%	96.7%	93.3%
C=150	90%	93.3%	90%
C=200	83.3%	86.7%	86.7%

Table 3. Influence of different SVM parameters

In our experiments, the optimum parameter values are get by comparing different kernal function and penalty factors.

To sum up in this part, brain CT Computer Aided classification & Diagnosis software system was discussed.

Based on the mainly 2 references discussion and analysis, we solved the main steps of CT image process, like image reading, image segmentation, feature extraction and feature-based classification steps. This chapter's first contribution is that a coarse-to-fine classification is proposed. And the main part (NCut-based segmentation and SVM classifier) are illustrated. For the CAD system, firstly by extracting features like colour histogram, edge and texture features and then using SVM classifier.

Fig. 6. Brain tumor

The specific method used in this chapter is NCut segmentation, multi-feature exaction and SVM classification. And the software tools used is Matlab7.0 and VC6.0 programming, compiling and debugging environment.
The software works well in Matlab7.0 for current data. What's New and good: Combined NCut segmentation and SVM classification.

3. Selective higher level classification

In the case that we get a CT image and the higher level class like the imaging part and the specific patient of the input image is unknown, a coarse CT image classification is proposed. And the basic idea is shown as Fig. 7.
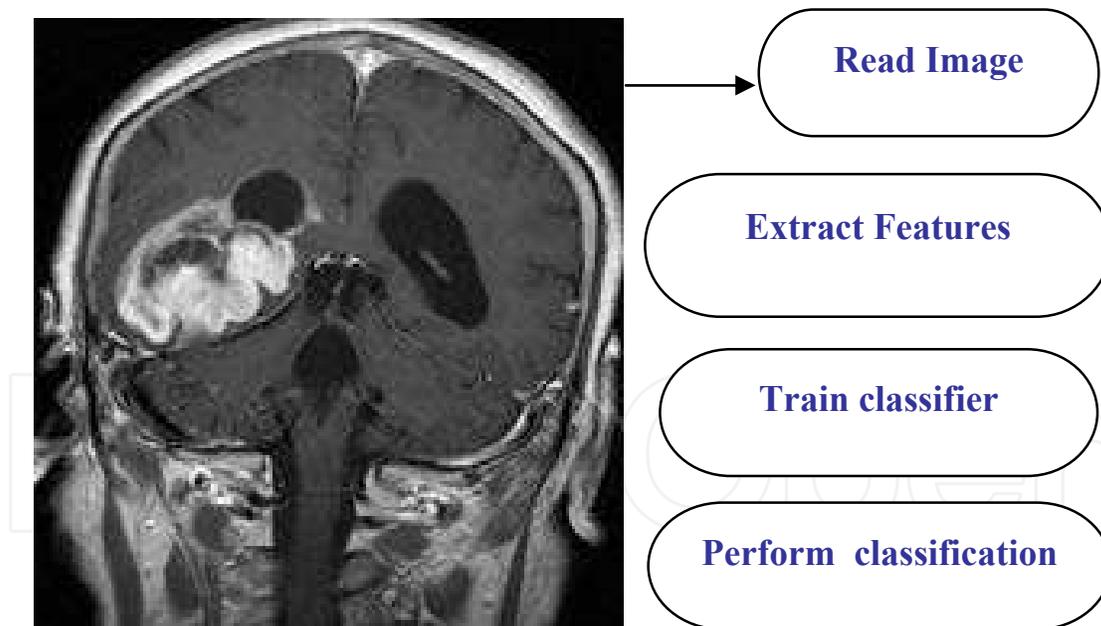
Fig. 7. Flowchart of coarse classification

For the coarse classification of the input image, grey features are used. First, the CT image is input and some normalizing work is done so as to make the size or resolution of the CT image to be uniform.
Then histogram of the input CT image is calculated and plotted. Based on histogram data and its statistical features like mean, variance, etc, the classification information is given out. Then based on the following equations (i.e. the Euclide-distance-based classification).

$$X_{train} = \{x_{tn1,}x_{tn2,}\cdots,x_{tnm,}\}$$

$$X_{test} = \{x_{tm1,}x_{tm2,}\cdots,x_{tmm,}\}$$

Where m is the dimension of the feature vector.
And the euclide-distance based classifying procedure can be described as:

For k=1 to numofclass

$$\text{Compute } d_{euk} = \sqrt{\sum_{i=1}^{m}(x_{tni} - x_{tmi})^2}$$

And find the minimum d_{euk} and classify the input image as k[th] class.

For a given input CT image, it is used either as training samples or test sample. In the latter case, then the resultant class label is given out the image is saved in the proper folders. (Note in some cases this pre-processing can be skipped if the exact information of imaging part is known.)

Imaging body part	Back	head	face	stomach	pelvis	chest
Data size	1402MB	403MB	89.2MB	52.9MB	39.6MB	477MB
Number of patients and sex portion	18 10 males and 8 females	37 20 males & 17 females	18	10 6 males and 4 females	3 (all females)	13(7 males and 6 females)
Total image size	1.16GB					

Table. 4. Descripton of the dataset used for coarse classification

Last the coarse classification results is given out in table 5.
Using histogram features as the main discriminitive base and te Euclide distance as the classifying criteria, we get the resultant resuts shown in table 5. One can see the precision rate is relatively high and acceptable. Thus we draw the conclusion that the propsoed coarse classificaton is simple and effective. This coarse classification may be very useful for the the following CT image-based disease detection and diagnosis.

4. Discussions of the novel algorithm for CAD system

The CAD system consists of two separate components. The first one is a coarse classification subsystem which is implemented by global feature extraction and Euclide-distance based classifier.
The second subsystem is the part that is composed of image segmentation, feature extraction, classifier training and classifier test. NCut is one of the novel proposed segmentation algorithms. Actually, some newly occurred algorithm can be used to

	stomach	head	pelvis	Back	face	chest
Total sample number	52.9MB	1346	131	450	320	1526
# of training samples	34	270	27	90	64	306
# of training samples	134	1076	104	360	256	1220
# of correct classified images	121	1035	100	353	213	1218
Precision rate	90.30%	90.19%	96.15%	98.08%	83.20%	99.84%
Total time cost	Approximately 355 seconds					

Table 5. Coarse classification results

substitute the NCut image segmentation according to the system needs. U. von Luxburg proposed using sparse representation to implement the image segmentation task. J. Mairal used Sparse signal models for local image discrimination tasks, proposing an energy formulation with both sparse reconstruction and class discrimination components, jointly optimized during dictionary learning. The approach improves over the state of the art in texture segmentation experiments using the Brodatz database, and it paves the way for a novel scene analysis and recognition framework based on simultaneously learning discriminative and reconstructive dictionaries. Our future work can be to use the sparse representation substitute our Ncut based segmentation provided that the newly proposed algorithm is proved to be better than our method.

For the classifier part, the SVM classifier has been proven to be good enough for the task. And future work can be done to improve the processing speed and also to improve the data amount that the system can handle. Therefore, parallel SVM classifier design and implementation is our future work field.

5. Conclusion

From the simulation results, we draw the conclusion that the NCut-based segmentation is correct and the parameter setting is reasonable. And this system can help doctors to make a reasonable and correct decision.

Diagnosis software was designed. For about 500MB image dataset we tested the software. The time cost is about 350 seconds and the average correct rate is about 90%. Actually 1.17GB image data was provided to be tested. This much detail work should be done.

There is a predefined parameter (the number of segmentation) for NCut segmentation, currently we set the number of segmentation to be 10 parts for brain CT image. In future work, much more detail work should be done to make the parameter more adaptive for other parts' CT image.

Although the software work well for the current software environment and dataset but for newly matlab version we met some portable problem since the NCut part only works on Matlab7.0 version and what's more important is that more modification should be

done to make the software more flexible in order to make it work without matlab platform.

On the one side, future work should be focus on the multi-kernel learning so as to improve the performance of the SVM classification.

On the other side, coarse-to-fine classification for medical CT image need be done for large amount of raw data. The coming medical CT image retrieval based on imaging body part and also Computer Aided classification is undergoing developing. We propose to parallel the traditional Euclidean distance-based coarse classification and implement it in the parallel platform or even the internet-based cloud environment in order to put the image into their corresponding imaging part fast and cost-effectively. Then fine segmentation based on NCut and the specific part's biological information, and lastly SVM classifier should be used to detect and analyze the ill tissue.

Moreover, much more data should be analyzed and the software development can be developed using merely C or Java platform in order to make the software product more portable and can be used in the newly occurred cloud computation environment.

6. Acknowledgment

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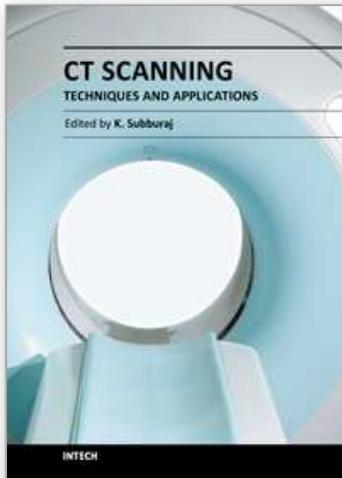
CT Scanning - Techniques and Applications

Edited by Dr. Karupppasamy Subburaj

Since its introduction in 1972, X-ray computed tomography (CT) has evolved into an essential diagnostic imaging tool for a continually increasing variety of clinical applications. The goal of this book was not simply to summarize currently available CT imaging techniques but also to provide clinical perspectives, advances in hybrid technologies, new applications other than medicine and an outlook on future developments. Major experts in this growing field contributed to this book, which is geared to radiologists, orthopedic surgeons, engineers, and clinical and basic researchers. We believe that CT scanning is an effective and essential tools in treatment planning, basic understanding of physiology, and and tackling the ever-increasing challenge of diagnosis in our society.

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