Image Mining in Fuzzy Model Approaches Based Random walker algorithm Brain Tumor Analysis (Meningioma Analysis)

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ABSTRACT - Gratified-built image recovery (GBIR) has twisted into an important and active potentialresearch field with the advance of multimedia and imaging technology. It makes use of image features, such as color, texture and shape, to index images with minimal human intervention.A GBIRsystem can be used to locate medical images in large databases. In this paper we propose a GBIR system which describes the methodology for retrieving digital human brain magnetic resonance images(MRI)based on textural features and the Adaptive Neuro-Ambiguous Inference System (ANAIS) learning to retrieve similar imagesfromdatabase in two categories: normal and tumoral.A fuzzy classifier has been used, because of the uncertainty in the results of classifier and capacity of learning.Adaptive Neuro-Fuzzy Inference System (ANAIS) is a good candidate for our categorization problem. Our proposed GBIR system can locate a query image in the category of normal ortumoralimages in the online Recoverypart. This research uses the knowledge of the GBIR approach to the application of medical decision support and discrimination between the normal and abnormal medical images based on features. This article and compare the results of the proposed method with the GBIR systemsused in recent works. The experimental results indicate that the proposed method is reliable and has high image recovery Random Walker Algorithm(RWA)efficiency compared with the previous work.

Keywords - Image Mining; GBIR;RWA; Feature extraction; ANAIS; Magnetic Resonance Image;

I. INTRODUCTION

Growth of medical image databases is enormous in the past few years. In the medical field, digital images such as computed tomography (CT), magnetic resonance imaging (MRI), ultrasound (US), nuclear medical imaging, endoscopy and microscopy, which were used for diagnostics or therapy are produced in medical centers ever increasingly and result in a large volume of data [1].A large number of existing image databases are indexed by text annotations that routinely contain only patient demographic details such as age, gender, date of study, modality. Manual methods to retrieve required image from the database with more comprehensive text annotation is tedious and time consuming [2]. In contrast, Gratified Based Image Recovery (GBIR) systems allow users to query based on the image content (i.e. image-derived features) rather than the related text annotation.

Systems for content-based image Recovery have been introduced in the early 1990s [3]. Content-based image Recovery uses the visual contents of an image such as color, shape and texture to represent and index the image. In a typical content-based image Recovery system, the visual contents of the images in the database are extracted and described by multi-dimensional feature vectors. The feature vectors of the images in the database form a feature database. The similarities or distances between the feature vectors of the query example and those of the images in the database are calculated. The Recovery is then performed with the aid of an indexing scheme. The indexing scheme provides an efficient way to search within image database for similar individual to the query image in order to return the relevant images. The general system setup for GBIR is shown in Figure 1. Generally speaking, GBIR aims at developing techniques that support effective searching and browsing of large image digital libraries on the basis of automatically derived image features [4].

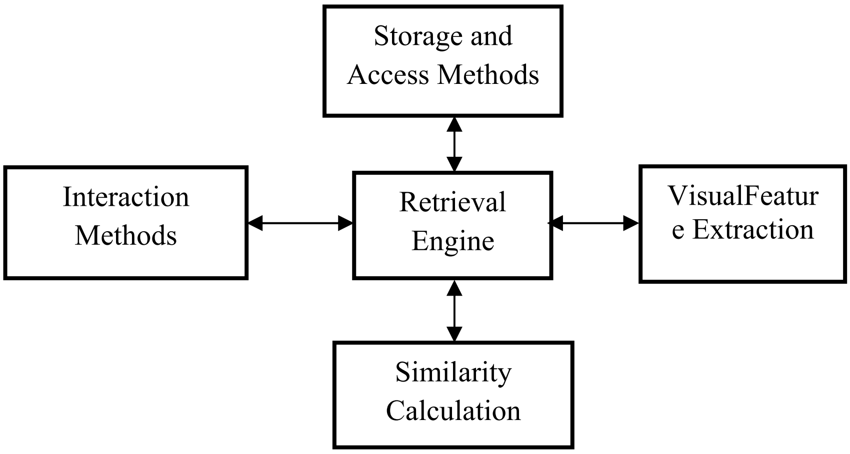


Figure 1. A general scheme for GBIR systems

In GBIR systems, statistical classification methods can group images into semantically meaningful categories using low level visual features such as color, shape and texture, so that semantically-adaptive searching methods applicable to each category can be applied [5]. Color features are computed by color moment and color histogram [6]. Shape features are calculated after images have been segmented into regions or objects [7, 8]. Shape information is captured in terms of edge images computed using Gradient Vector Flow fields [9]. Invariant moments are then used to record the shape features [9]. Texture features are computed by statistical Tamura feature and multi resolution filtering techniques such as Gabor and Wavelet Transform, characterize texture by the statistical distribution of the image intensity [9, 10, 11].

In [12, 13], a GBIR system for brain lesions has been proposed based on the analysis of histogram features, derived from brains. An image Recovery method combined color and texture features is proposed in [14].The other works have shown the GBIR systems with the use of different classifiers to group the images in database via supervised techniques such as artificial neural networks and support vector machine (SVM) [10,15,16] and Naïve Bayes classifier [17] , and also unsupervised categorization techniques such as Self Organizing Map (SOM) [18], and fuzzy c-means combined with feature extraction techniques [19,20].Other categorization techniques, such as k-nearest neighbors (KNN) also group pixels based on their similarities in each feature image.

Some GBIR systems subdivide the image into predefined blocks or more commonly, partition the image into different meaningful regions by applying a segmentation algorithm. In both cases, each region of the image is represented as a vector of feature values extracted from that region. Other GBIR systems extract salient points, which are points of high variability in the features of the local pixel neighborhood. With salient point-based methods, one feature vector is created for each salient point. Then a similarity metric is used to rank the images.

A. PROBLEM ANALYSIS

In this paper we propose a GBIR system for brain magnetic resonance images that is based on Adaptive Neuro-fuzzy Inference System (ANAIS) learning and can categorize an image as normal and tumoral. We use three sets of statistical features including “first order gray level statistics”, “statistics extracted from Gray Level Co-occurrence Matrix (GLCM)” and “2D statistics” to extract textural features which has less computational complexity in comparison of other methods like wavelet or Gabor filter. After feature extraction, Principal Component Analysis (PCA) has been applied to effectively reduce the dimensionality of data which directly reduces the computational cost. In categorization part, we use ANAIS as a supervised algorithm to categorize MR images. A query image is introduced to the system and it is grouped as a normal or tumoral image in order to return the relevant images. Finally, using a relevance feedback, we improve the effectiveness of our Recovery system.

B. SECTION ANALYSIS

This paper is organized as follows.Section 2 describes the materials and methods. In this section the proposed GBIR algorithm is presented. The methods for feature extraction and reduction as well for categorization and also the online Recovery part of the system and significanceresponse will describe in this section. In section 3, experimental results areshown. The results are discussed is section 4, while conclusion is mentioned in section 5.

II. IMPLEMENTATION OF RESEARCH

A. PROPOSED ANALYSIS

The proposed GBIR framework is shown in Figure 2. The images are kept in a database named Image Database. The method in this work contains three major stages: image analysis, image Recovery and relevance feedback. The objective of the image analysis stage is to examine the textural features of MR images in database, and then test the statistical significance of the differences between normal and abnormal MRIs.These discriminating features are selected to construct a texturaldescriptor of MRIs in the database. The Principal Component Analysis (PCA) is then applied to effectively reduce the dimensionality of data. After dimension reduction, we use Adaptive Neuro-Ambiguous Inference System (ANAIS) as a supervised algorithm to categorize the feature descriptors of MR images. This process is related to the offline analysis in the proposed GBIR system. In online image recovery, a query image is introduced to the system. The feature descriptor is extracted from the query image. Then it is indexed as a normal or tumoral image in order to return the relevant images. Finally, we use the relevance feedback to improve the Recoveryresult. The performance of the GBIR system is then evaluated. The detailed steps and components of the experiment are described in the following sections.

B. FLOW CHART

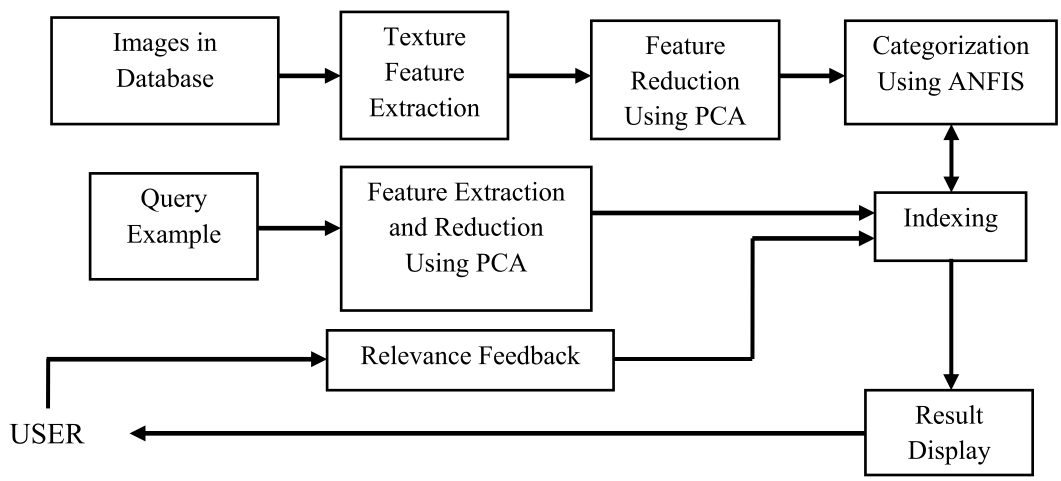
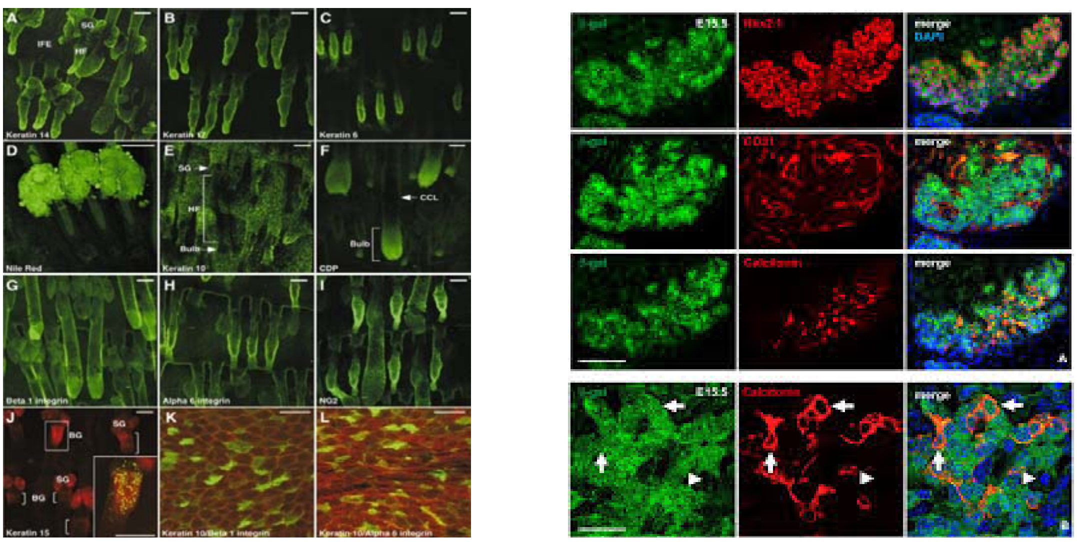


Figure 2. Block diagram for the proposed GBIR system

C. ORGANIZING THE NECESSARY DATABASE

The experiments are carried out on a real human brain MRI dataset, which includes 939 images covering normal and tumoral categories which 101 images are selected randomly as query images in experiments. So, the input dataset contains 838 axial images which 682 images are normal and 156 images are tumoral. These images have been collected from the SMC Trichy Medical School website. Figure 3 shows some samples from the used data for normal and tumoral images.



(a) (b)

Figure 3. Sample MR images from the database, a) normal image and b) image with tumor

D. FEATURE EXTRACTION

Feature extraction is the fundamental basis of GBIR systems. Features of an image are the properties that describe the content of an image which consist of visual features extracted from the image and they are distinguishing primitive characteristics or attributes of an image. Representation of images needs to consider which features are most useful for representing the contents of images and which approaches can effectively code the attributes of the images. Feature extraction of the image in the database is typically conducted off-line, so computation complexity is not a significant issue.This paper concentrates on textural analysis for the content-based Recovery of MR images.

We have calculated seven features from “first order gray level statistics” as follows:

1. *mean :* $m = \sum_{i=0}^{255} z_i P(z_i)$
2. *standard deviation :* $\mu_2(z) = \sum_{i=0}^{255} (z_i - m)^2 P(z_i)$
3. *Contrast :* $R = 1 - \frac{1}{1+\sigma_z^2}$,
4. *Skewness :* $\mu_3(z) = \sum_{i=0}^{255} (z_i - m)^3 P(z_i)$
5. *Kurtosis :* $\mu_4(z) = \sum_{i=0}^{255} (z_i - m)^4 P(z_i)$
6. *Uniformity :* $\sum_{i=0}^{255} P^2(z_i)$
7. *Entropy :* $-\sum_{i=0}^{255} P^2(z_i)\, log_2\,(P(z_i))$

$P(z_i)$is the normalized image histogram and σ_z^2 is the image variance.

Also, the gray level co-occurrence matrices (GLCM) are calculated for all the images in the database. GLCM is built by incrementing locations, where certain gray levels i and j occur at a distance “d”apart from each other [32]. Texture features that can be extracted from gray level co-occurrence matrixare:

1. *Maximum probability :* $Max_{ij}\ (c_{ij})$
2. *Element difference moment of order 2 :* $\sum_i \sum_j (i-j)^2 (c_{ij})$
3. *Inverse element difference moment of order 2 :*$\sum_i \sum_{j \neq i} (c_{ij})/(i-j)^2$
4. *Uniformity :*$\sum_i \sum_{j \neq i} (c_{ij})^2$
5. *Entropy :*$-\sum_i \sum_j c_{ij} \log_2\ (c_{ij})$

where c_{ij} is the gray level co-occurrence matrix.

Finally, we have calculated seven features from “two dimensional statistics”, that they are rotation, translation and scale invariant values, as follows:

1. $\varphi_1 = \eta_{20} + \eta_{02}$
2. $\varphi_2 = (\eta_{20} - \eta_{02})^2 + 4\,\eta_{11}^2$
3. $\varphi_3 = (\eta_{30} - 3\,\eta_{12})^2 + (3\,\eta_{21} - \eta_{03})^2$
4. $\varphi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2$
5. $\varphi_5 = (\eta_{30} - 3\,\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\,\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$
6. $\varphi_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\,\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})$
7. $\varphi_7 = (3\,\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\,\eta_{12} - \eta_{30})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$

andη_{pq} is the normalized central moment as:

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}} \quad , \quad \gamma = \frac{p+q}{2} + 1$$

whereμ_{pq} is the central momentof order *p+q*.

After computing these features, they are grouped into feature vectors of the corresponding images in database and used for the next step in the proposed GBIR framework.

E. FEATURE REDUCTION

Our task of content based image Recovery typically focuses on representing the images in the training database and the test database in a relatively high dimensional feature vector. Feature set of high dimensionality causes the “curse of dimensionality” problem in which the complexity and computational cost of the query increase exponentially with the number of dimensions. To reduce the dimensionality of a large feature set, the most widely-used technique in image Recovery is principal component analysis (PCA)to eliminate those dimensions that have low impact on the categorization process. This technique is also called Karhunen-Loeve Transform (KLT) .

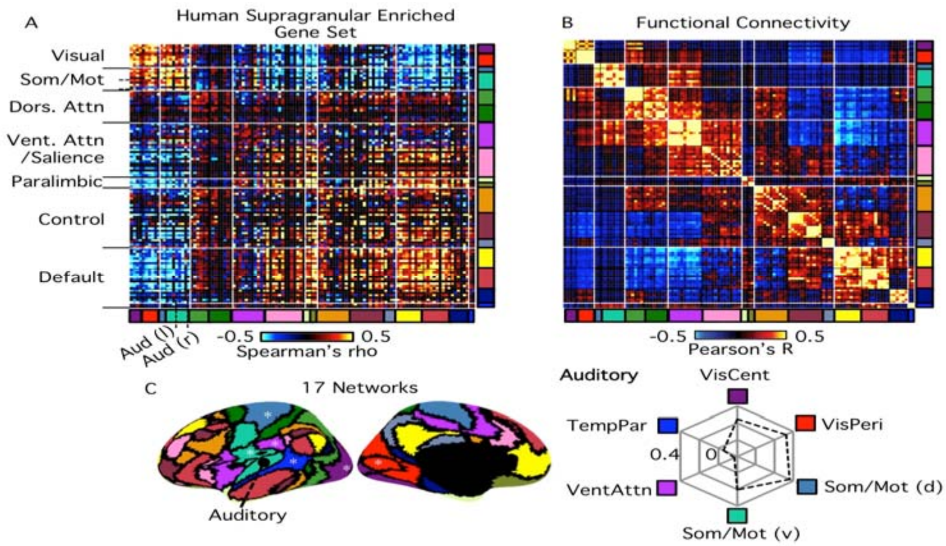


Figure 2.2. a) ANAISimages, b) Examples of recovered images

The goal of principal component analysis is to specify as much variance as possible with the smallest number of variables. Principal component analysis involves transforming the original data into a new coordinate system with low dimension, thus creating a new set of data. The new coordinate system removes the redundant data, and the new set of data may better represent the essential information. Limiting the feature vectors to the components selected by the PCA, leads to an increase in accuracy rate and also increases the speed of Recovery. So, to reduce the complexity of the proposed system and dimensionality of the features matrix, we use PCA for feature reduction.

F. EXPERIMENT ANALYSIS

In this experiment, we have extracted 19 features for each image in database. So, there are 19 Eigen values of the features matrix which are calculated during PCA algorithm. We have chosen 6 output features that are more valuable. Selected features have been used to apply to the proposed classifier in the next stage.

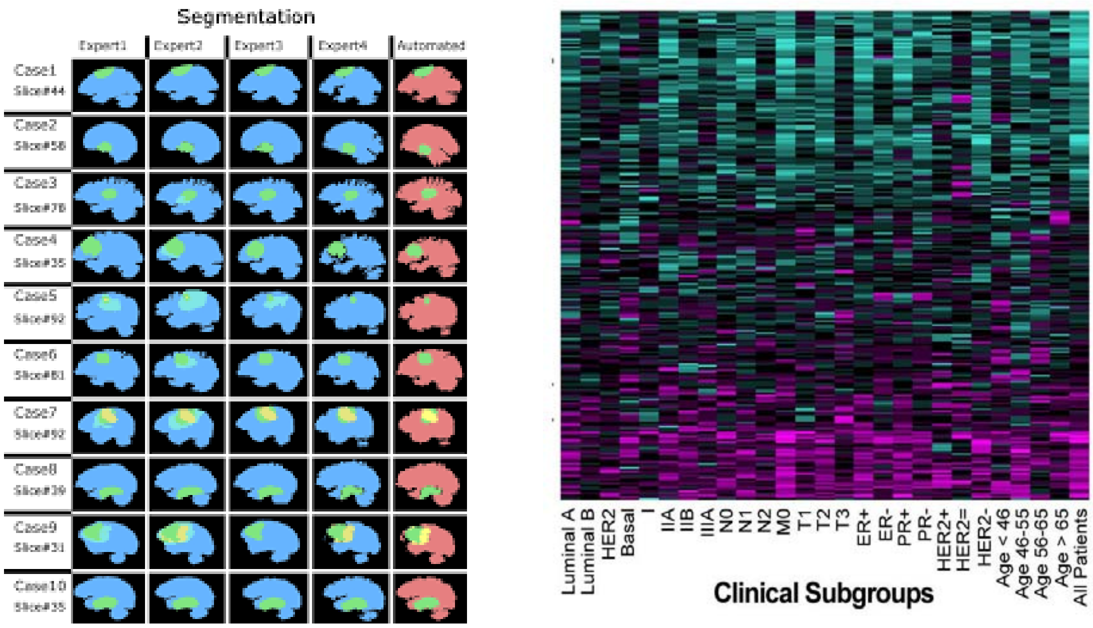


Figure 2.3. a) ANAIS Analysis b)GBIR recovered images

G. IMAGECATEGORIZATION

Grouping images into meaningful categories using low-level visual features, is a challenging and important problem in the GBIR. A successful categorization of images greatly enhances the performance of a content-based Recovery system by filtering out irrelevant classes.One attempt to solve the image indexing problem is the hierarchical indexing scheme proposed by Zhang and Zhong, which uses a self-organization feature map, SOFM, to cluster images into groups of visually similar images based on color and texture features. However, the success of such clustering-based indexing is often limited, largely due to low-level feature-based representation of image content built a classifier for the categorization of database images into two groups of city and landscape. They have used a weighted k-NN classifier for categorization. In a similar way, they proposed a large framework of hierarchical categorization of vacation images into several groups, using the Bayesian methodology.In other work, a three-layer neural network with sigmoid nonlinearity has been used to perform the image categorization for two groups of indoor and outdoor images using the combination of multiple low-level visual features.

H. PROCESSING METHOD

The categorization involves two steps: training and testing. In the training stage, the system is fed with the output feature vectors from PCA, of all the MR images in database, along with the desired output for training the network. The FIS (Fuzzy Inference System) is generated that creates an initial model for ANAIS training by first applying subtractive clustering on the data. The train FIS optimization method is chosen as hybrid; that includes least square type along with back propagation gradient descent algorithm which trains the membership function parameters to emulate the training data. The next step is to test the created model with the help of test data. ANAIS categorizes the MRI database into two certain group consisting of normal images and tumoral images.

I. RECOVERY OF DESIRED IMAGES

In online image Recovery part, the user submits a query example to the Recovery system in search of desired images. The system represents this example with a feature vector. The output feature vector from PCA of the query, is applied to the trained ANAIS in the offline part as a test input. ANAIS categorizes the query as a normal or tumoral image. Finally, the system returns the images of the related class to the user.

After categorization, we can also compute the distance between the feature vector of the query example and those of the images in the related class, using a similarity measure. Then, the system ranks the search results and returns the results that are most similar to the query examples.

If there is a false categorization, the corresponding label in the network is modified in a learning process using captured knowledge from user's interactions in the relevance feedback process. In the next section, we discuss in detail about the relevance feedback.

J. IMPROVING RESULTS USING RELEVANCE FEEDBACK

Relevance feedback was originally developed for improving the effectiveness of image Recovery systems. The semantic gap between low levelvisual features and high level human perception andinterpretation has limited the usefulness of most of existingGBIR. Many year studies have made it clear that the usershould be involved as part of the Recovery process to reducethe semantic gap.It is an iterative approach which interacts with users in each search and Recovery cycle.

In a typical Recovery system, for a given query, the system returns initial results based on pre-defined similarity metrics. Then, the user is required to identify the positive examples by labeling those that are relevant to the query. The system subsequently analyzes the user's feedback using a learning algorithm and returns refined results.

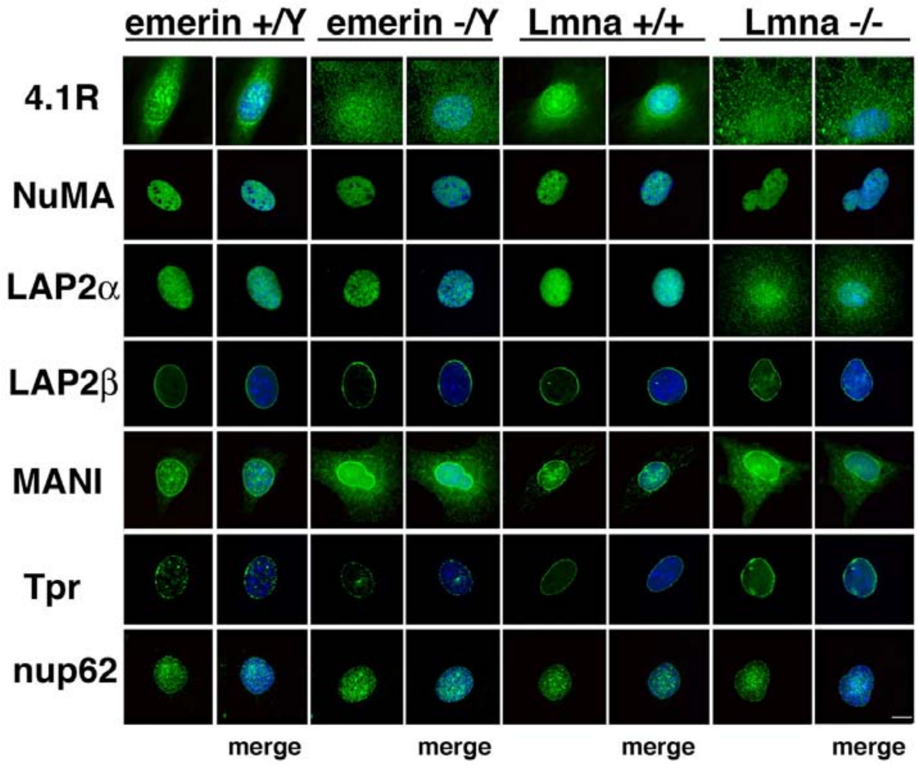
K. ANALYSIS SYSTEM

In our research, for a given query, the Recovery system returns the MR images of the related class (i.e. normal or tumoral) to the user. Then, the user is required to check the result of query categorization. If there is a false categorization, the user will add the query image to the database with the corresponding label. Then, the new database will be used to train and test the ANAIS classifier and the next query images will be applied to the new trained ANAIS in online Recovery part. This process is continued iteratively until the user is satisfied with the Recovery results displayed or there will be no changes in.

III. RESULTS

The experimental results of the proposed algorithm are shown in this section. The algorithm described in this paper is implemented in MATLAB, version 7.10.We used a personal computer with CPU 2.27 GHz, Core I5 processor and 4 GB of RAM under Windows 7 operating system. The results of off-line feature extraction and categorization of images in database and also the online query Recovery are as following:

A. RESULTS OF IMAGE CATEGORIZATION



As mentioned in section A, the input dataset for categorization contains 838 MR images, which 682 images are normal and 156 images are tumoral. We used 40 percent of data (i.e. 335 images) as training data set for ANAIS, while the remaining images (i.e. 60 percent including 503 images) were the checking data set for validating the identified ANAIS. The number of membership functions assigned to each input of the ANAIS was set to three. Since the number of output features extracted from each image in database is 6, the number of ANAIS rules is 729. Also we set the desired output of the ANAIS algorithm to “zero” for a normal image and “one” for an image with tumor. Then we take the “round” of training and test outputs to show the results.

The result of the proposed classifier is given in Tables 1 and 2. Table 1 shows the training result of the classifier and the result of test images categorization is given in Table 2. Also, the categorization accuracy for two different image classes is shown in Table 3.

Table 1. Training result of the ANAIS classifier

Training Images in Database (total=335)			
	Normal Class	Tumor Class	None
273 Normal Images	273	0	0
62 Tumoral Images	0	62	0

Table 2. Test result of the ANAIS classifier

Test Images in Database (total=503)			
	Normal Class	Tumor Class	None
409 Normal Images	404	1	4
94 Tumoral Images	14	78	2

Table 3. Percentage of categorization based on normal and tumor classes for ANAIS classifier

Number of normal images categorized as normal class (percentage)	98.77%
Number of tumor images categorized as tumor class (percentage)	82.97%

Considering the analysis ofthe experimental results, which is shown in Table 3, thecategorization accuracy of detecting the normal imagesin the normal class is 98.77% and the percentage of categorizing abnormal images is 82.97%. These results are acceptable with comparison of previous works based on categorizing into two groups on the same MRI database that will be shown later.

B. RECOVERY EFFICIENCY

The online query Recovery is carried out on 101 MR images including normal and tumoral images, which are selected randomly as query images in experiments. The result of online image Recovery is shown in Table 4. Also, Table 5 shows the Recovery efficiency based on retrieved normal and tumor images.

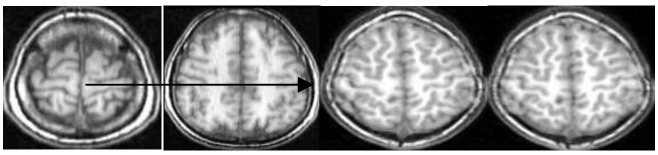
Table 4. The results of online query Recovery in proposed method

Input Query (total=101)			
	Normal Class	Tumor Class	None
65 Normal Images	61	4	0
36 Tumoral Images	3	33	0

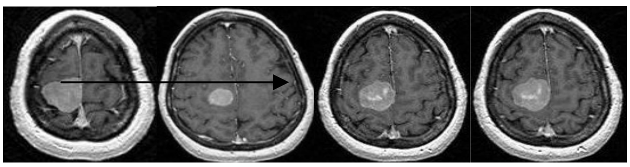
Table 5. Percentage of query Recovery based on retrieved normal and tumor images in proposed method

Number of normal queries retrieved as normal (percentage)	93.84%
Number of tumor queries retrieved as Tumor (percentage)	91.67%

As it is possible to see, the query Recovery of the proposed method shows the good results. According to Table 4, it is obvious that 61 normal images from 65 normal queries have been placed in the correct group, and 33 tumoral images from 36 queries with tumor have been retrieved using the proposed method. Figure 4 shows the examples of retrieved images with sample queries.



(a)



(b)

Figure 4. a) Sample query images, b) Examples of retrieved images

C. RESULT OF RELEVANCE FEEDBACK

As mentioned in section C, the algorithm of the relevance feedback process is proposed as following:

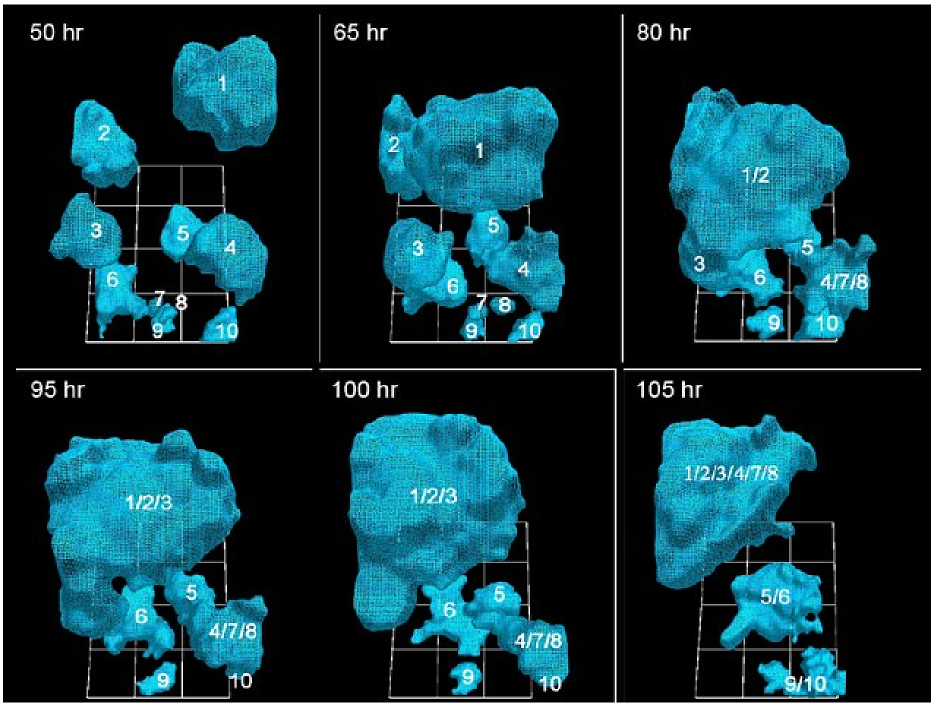


Figure 4.1 Overall Result

1. Checking the result of detected category (normal or tumor) of the query in the Recovery process by the user
2. If there is a false categorization, then the user will add the query to the database
3. Training and testing the ANAIS classifier with new database (old database + added query)
4. Using the new trained ANAIS in the Recovery engine of the system
5. Doing image Recovery with the same query or different queries
6. If the result of query categorization is correct, or the user is satisfied with the result, then the feedback process stops.
7. Else, going to the step 2.

Regarding to this algorithm, the Recovery engine will be stronger in each iteration and lead to better performance of the GBIR system.

As shown in Table 4, some normal or tumoral images were categorized in the incorrect class in online Recovery engine. The user performs the mentioned algorithm of relevance feedback for such query examples. Using this algorithm, in step 3, membership functions of the ANAIS classifier will be modified. In step 4, the new trained ANAIS can improve Recovery efficiency of the system. In our experiment, the relevance feedback process was done according the above mentioned, and we obtained the Recovery accuracy equal to 97.03% after one iteration. Table 6 shows the feedback results.

Table 6. The result of relevance feedback after one iteration

Input Query (total=101)			
	Normal Class	Tumor Class	None
65 Normal Images	65	0	0
36 Tumoral Images	3	33	0

IV. DISCUSSIONS

Finally, the proposed GBIR system retrieved a query as a normal or tumoral image. Considering the analysis of the experimental results, which are shown in Tables 4 and 5, the accuracy of query Recovery for the normal queries retrieved as normal is 93.84 percent and for the tumor queries retrieved as tumor is 91.67 percent. According to Table 4, the total accuracy of the query Recovery in our proposed system is 93.07 percent which using the relevance feedback, weenhanced the results of Recovery to 97.03%. These results are acceptable and reliable with comparison of recent works . In this section we have implemented the recent GBIR methods on the same MRI database to compare the results with our proposed method. Table 7 shows the Recovery accuracy of our method and the recent works, on the same MRI database. Note that the relevance feedback has not been considered in the comparison of methods in Table 7.

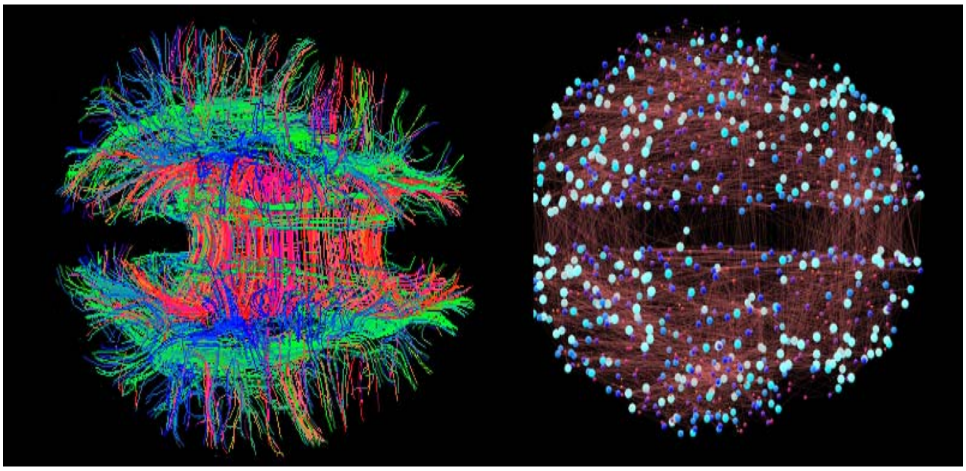


Figure 4.1 GBIR system repossessed Images in computer analaysis

A. DATASET ANALYSIS

The GBIR system using the Naïve Bayes classifier for image categorization [17], with the extracted features in our method gives 90.09% rate for the query Recovery. This technique also gives the 86.13% rate with use of Principal Component Analysis (PCA) of the extracted features in the Recovery part. The use of PCA features and categorization through SVM in [16], results 92.07%.The same work [21] with the extracted features in our method and K-nearest neighbor (KNN) classifier produced 73.93% rate. We considered 100 nearest neighbors to each query image. The GBIR system using FCM clustering and query Recovery with calculating the Euclidean distance between the query features and center of classes [20], found 70.29%.The other work using the Singular Value Decomposition (SVD) and SVM classifier with different kernels (polynomial, radial, and linear), has been done on mammograms in [15]. Using this method on the MRI database, results the 89.10%, 66.33% and 92.07% rates for the image Recovery with polynomialkernel, radial basis function based kernel and linear kernel SVM respectively. The first 100 singular values in the SVD vector were kept for the composition of the feature vector.

Regarding to the GBIR system in [10,11], with the texture features extracted by Discrete Wavelet Transform (DWT) and then categorized through Back Propagating Neural Network and SVM classifier, gives 64.35% rate in both cases.

B. COMPARISON STUDY

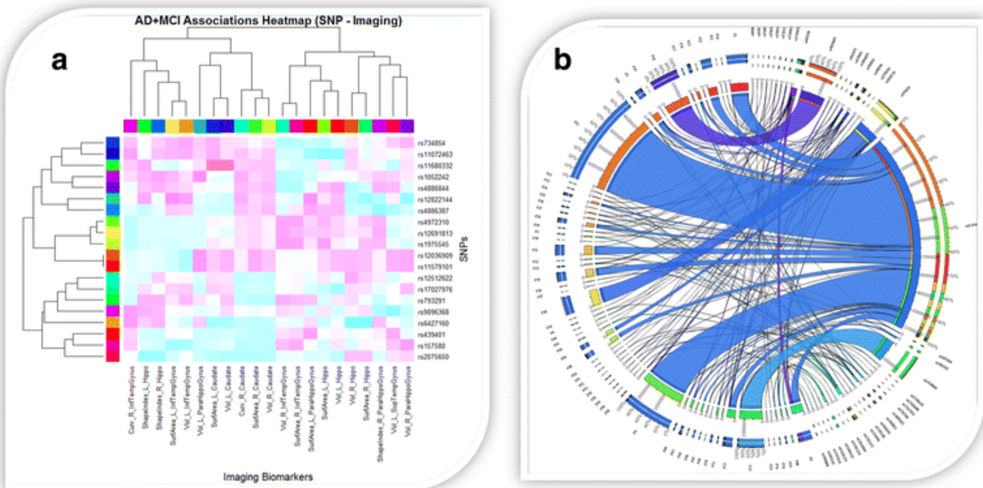


Figure 4.3 GBIR&ANAIS Comparison PWA,RWA

This comparison shows that the presented GBIR system has high image Recovery efficiency and less computation due to the feature reduction based on the PCA. According to the experimental results, our system is more reliable and acceptable than the GBIR systems introduced in related works on the same database.

Table 7. The Recovery efficiency of the proposed method compared with the recent works for the same MRI database

Method	**Feature** Extraction	Feature Reduction	**Similarity Measure/Classifier**	**Recovery Accuracy**
Our Technique	**1) first order gray level statistics 2) statistics extracted from GLCM 3) 2D statistics**	**PCA**	**ANAIS Classifier**	**93.07%**
Method 1 [17]	1) first order gray level statistics 2) statistics extracted from GLCM 3) 2D statistics	-----	Naïve Bayes	90.09%
Method 2 [17]	1) first order gray level statistics 2) statistics extracted from GLCM 3) 2D statistics	PCA	Naïve Bayes	86.13%
Method 3 [16]	1) first order gray level statistics 2) statistics extracted from GLCM 3) 2D statistics	PCA	SVM	92.07%
Method 4 [21]	1) first order gray level statistics 2) statistics extracted from GLCM 3) 2D statistics	----	KNN	73.93%
Method 5 [20]	1) first order gray level statistics 2) statistics extracted from GLCM 3) 2D statistics	----	FCM Clustering and Euclidean Distance	70.29%
Method 6 [15]	SVD	----	SVM with polynomial kernel	89.10%
Method 7 [15]	SVD	----	SVM with RBF kernel	66.33%
Method 8 [15]	SVD	----	SVM with linear kernel	92.07%
Method 9 [10,11]	DWT	----	MLP	64.35%
Method 10 [10,11]	DWT	----	SVM	64.35%

Our proposed method using the ANAIS classifier specifies the class type of each query image which is applied to the online Recovery engine by user. This process takes a very short time about 0.25 second and presents the valid results.

V. CONCLUSIONS

In this paper, we presented a content based medical image Recovery system for brain magnetic resonance images that was based on Adaptive Neuro-Ambiguous Inference System (ANAIS) learning and could categorize an image as normal and tumoral. We used three sets of statistical features which contains "first order gray level statistics", "statistics extracted from Gray Level Co-occurrence Matrix (GLCM)" and "2D statistics". After feature extraction, the Principal Component Analysis (PCA) was used to effectively reduce the dimensionality of data. For categorization, we used ANAIS as a supervised learning method, which was helpful to get very promising results in grouping the normal images and images with tumor.

In online image Recovery part, the user submits a query example to the Recovery system in search of desired images. The system represents the example with a feature vector and the output feature vector from PCA of the query, is applied to the trained ANAIS in the offline part. ANAIS categorizes the query as a normal or tumoral image. Finally, the system returns the images of the related class to the user. If there was a false categorization, we would use the relevance feedback using captured knowledge from user's interactions, to modify the images label in the network. The relevance feedback will improve the effectiveness of our Recovery system.

The proposed system can be used as a medical decision support system to find normal or tumoral MR images. The benefit of our system is to assist the physician to make the final decision without hesitation.

The experiments were carried out on a real human brain MRI dataset, which includes 838 images covering normal and tumoral categories and 101 images were used as query images in the experiments. According to the experimental results, we found that the proposed GBIR system with the ANAIS learning algorithm, gives better results than the systems presented in recent works, for the same database. Our work produced 93.07 % rate for the query Recovery which using the relevance feedback, we improved the results of Recovery to 97.03%. This result shows that the proposed method can make an accurate and robust content based image Recovery system and it is a powerful method in comparison with the previous works on the same data.

In the previous works, the GBIR system using the Naïve Bayes classifier for image categorization [17], gave 90.09% rate for the query Recovery and found the 86.13% rate with use of Principal Component Analysis (PCA) of the extracted features in the Recovery part. The use of PCA features and SVM classifier in [16], produced 92.07% rate.In the same work with KNN classifier [21], the Recovery result was 73.93%. The use of FCM clustering and calculating the Euclidean distance between the query features and center of classes in [20], led to 70.29% rate.

Also we have compared our method with the GBIR system using the SVD features and SVM classifier with different kernels [15]. On the other hand, the image Recovery system with the DWT features and using MLP and SVM classifiers [10], were compared with our proposed method.

The stated results show that the proposed method can make an accurate and robust GBIR system. The performance of the image Recovery in this study shows the advantages of this technique: it is easy to operate, noninvasive and reliable.

There are many directions for future work. We believe that our system can be improved further by making improvements to features by extracting the Region of Interest (ROI) of images.

Regarding the type of images in database, the use of color and asymmetric features might be helpful and can be used in future work.Also, we can extend our developed technique for processing more abnormalities on brain MRI database to make the algorithm more practical.

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