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DICOM Image Retrieval Based on Neural Network Classification

B. Darsana[1] and G. Jagajothi[2]

[1]Department of Information Science & Engg., The Oxford College of Engineering, Bangalore

[2]Department of Information Technology, Periyar Maniammai University, Tanajore

[1]darsana.b@live.com

***Abstract*— Digital imaging and Communications in Medicine (DICOM) is a standard developed for handling large amount of pictorial information in Medical imaging. With the vast availability of medical imaging applications like computed tomography, magnetic resonance, digital radiography, radiation therapy and ultra sound, the need for storing, printing, transmitting and retrieving biomedical images became obligatory. As per the DICOM standard, the images are basically retrieved based on the textual information associated with every DICOM image. This research proposes Content based retrieval of DICOM images which will aid in retrieval of semantically relevant images without need for providing any additional information. This is achieved by classification based multimodal image retrieval. A combination of low level features and high level features are extracted for initial filtering of images. The classification of the images is done with the help of neural network where optimization process is incorporated for weight calculation which aids in effective classification of images. The relevance of classified images to query image is further optimized by using fuzzy c-means algorithm.**

***Index Terms*—Classification, Content-based Image Retrieval, DICOM, Multimodal Image and Neural Network**

I. INTRODUCTION

THE importance of Content-based image retrieval (CBIR) has attracted much research interest in the medical imaging field in recent years. The paramount challenge of semantic gap is bridged by Content-based Image Retrieval [1], which is one of the hot spots in the field of image retrieval. It extracts images' visual information by analyzing the images. However, the algorithm of a single visual image feature represents only partial property of the image [2], so search results have not been very good. In the extraction of combined features, traditional methods mostly extract manifold features from the original image. This has the disadvantage that the feature vector is too big and computational complexity is too high, especially for large databases.Medical images build essential portions for distinguishing and investigating dissimilar body structures and the diseases offensive them [3]. In particular, there has been growing interest in indexing biomedical images by content. Due to the lack of effective automated methods, however, biomedical images are typically annotated manually and retrieved using a text keyword-based search [4].

DICOM is the First version of a standard developed by (ACR) and National Electrical Manufacturers Association (NEMA). DICOM integrates scanners, servers, workstations, printers, and network hardware from multiple manufacturers into a picture archiving and communication system (PACS). A DICOM data object consists of a number of attributes, including items such as name, ID, etc., and also one special attribute containing the image pixel data. A single DICOM object can have only one attribute containing pixel data. For many modalities, this corresponds to a single image. Pixel data can be compressed using a variety of standards, including JPEG, JPEG Lossless, JPEG 2000, and Run-length encoding (RLE). Here, patient information can be stored with the actual image, although still a few problems prevail with respect to the standardization [5].

Throughout the world, rapid growth of computerized medical imagery using picture archiving and communication systems (PACS) in hospitals has generated a critical need for efficient and powerful search engines. In addition, the growing number of bio medical images in recent years increases the need for computerized systems which could help the radiologist in prioritization and in the diagnosis of findings. As an important complementary search approach, content based image retrieval (CBIR) has been one of the most vivid research areas in the field of computer vision over the last 10 years [6].

The size of most medical images are large which will need to be compressed before sending or collecting data because of the limitation of the bandwidth and capacity of the data saving space [7].

Medical image processing is the use of the algorithms and procedures for operations such as image enhancement, image compression, image analysis, mapping, geo-referencing, etc. The rapid development in medical research produces a continuous stream of new knowledge about disease processes, new therapeutic targets.

It plays a vital role in disease diagnosis and helps the medical practitioners during decision making with regard to the type of treatment.

The influence and impact of digital images on healthcare industry is tremendous and contributes a great deal in improved patient care [8].

From the biomedical imaging point of view, there are wide range of applications that are being developed in image producing departments such as Pathology, Hematology and Dermatology etc. In Pathology, most of the work has been done on color changes and texture of microscopic images. For serving case-based reasoning, a new approach to improve the efficiency of bio medical image retrieval task with the use of both low level as well as high level features along with relevance clustering is developed in this paper.

The rest of this paper is organized as follows: Section II describes the literature review, Section III focuses on the proposed approach to resolve the limitations identified in the literature survey, Section IV deals with the experimental setup and Section V concludes the paper, high lighting the advantages of the proposed approach.

II. LITERATURE REVIEW

Abolfazl Lakdashti and Hossein Ajorloo [9] have proposed a reinforcement learning method to enable a relevance feedback paradigm to evolve itself by user's feedback. The feature space of the medical images was partitioned into positive and negative hyper-cubes by the system. Each hypercube constitutes an individual in a genetic algorithm infrastructure. The rules take recombination and mutation operators to make rules for better exploring the feature space. The effectiveness of the rules was checked by a scoring method by which the ineffective rules would be omitted gradually and the effective ones survive.

Pan et al. [10] have proposed a notion of image sequence similarity patterns (ISSP) for medical image database. ISSP refer to the longest similar and continuous sub-patterns sequence. These patterns were significant in medical images because the similarity for two medical images was not important, but rather, it was the similarity of objects each of which has an image sequence that was meaningful. They designed the algorithms with the guidance of the domain knowledge to discover the possible Space-Occupying Lesion (PSO) in brain images and ISSP for similarity retrieval.

J. R. Smith and S.F. Chang [11] have proposed a fuzzy rule based method which determines which of the image features were more important than the other ones, by making a proper weight vector for the distance measure. For instance, for a given query image, large weights could be assigned to shape features, whilst texture features could be almost ignored by taking small weights.

For the training purpose, an algorithm was provided by which the system adjusts its fuzzy rule parameters by gathering the trainers opinions on which and how much the image pairs were relevant. For further improving the performance of the system, a feature space dimensionality reduction method was also proposed. To ensure that this method would increase the precision of the system, they have monitored the precision parameter in its training.

G. Quellec et al. [12] have proposed content-based image retrieval (CBIR) method for diagnosis aid in medical field. In the proposed system, images were indexed in a generic fashion, without extracting domain-specific features a signature was built for each image from its wavelet transform. These image signatures characterize the distribution of wavelet coefficients in each sub-band of the decomposition. A distance measure was then defined to compare two image signatures and thus retrieve the most similar images in a database when a query image was submitted by a physician. To retrieve relevant images from a medical database, the signatures and the distance measure must be related to the medical interpretation of images. As a consequence, they introduced several degrees of freedom in the system so that it could be tuned to any pathology and image modality.

B. Ramamurthy and K.R. Chandran [13] have proposed an efficient medical image data Retrieval from a huge content of medical database using one of the images content such as image shape, because, efficient content-based image Retrieval in the medical domain was still a challenging problem. The main objective was to provide an efficient tool which was used for efficient medical image retrieval from a huge content of medical image database and which was used for further medical diagnosis purposes.

Ramamurthy, B. and K.R. Chandran [14] have proposed an efficient image retrieval tool namely, "Content Based Medical Image Retrieval with Texture Content using Gray Level Co-occurrence Matrix (GLCM) and k-Means Clustering algorithms". This image retrieval tool was capable of retrieving images based on the texture feature of the image and it takes into account the Pre-processing, feature extraction, Classification and retrieval steps in order to construct an efficient retrieval tool. The main feature of this tool was used in GLCM of the extracting texture pattern of the image and k-means clustering algorithm for image classification in order to improve retrieval efficiency. The proposed image retrieval system consists of three stages i.e., segmentation, texture feature extraction and clustering process.

In the segmentation process, pre-processing step to segment the image into blocks was carried out. A reduction in an image region to be processed was carried out in the texture feature extraction process and finally, the extracted image was clustered using the k-means algorithm. The proposed system was employed for domain specific based search engine for medical Images such as CT-Scan, MRI-Scan and X-Ray.

Moments of images provide efficient local descriptors and have been used extensively in image analysis applications. Moments were able to provide invariant measures of shape. Jyothi et al [15] have proposed a efficient retrieval system using region-based image retrieval system, finding region in the pictures using image segmentation method by improved mountain clustering (IMC) technique and features were extracted using a set of orthogonal set of moment functions for describing images The performance of the proposed moments was analyzed in terms of Recall Rate and Retrieval Accuracy. Major constraints in chromosome classification are- mechanisms to optimize the retrieval process are not possible [16] and size of feature vector plays important role in performance of image retrieval.

The proposed approach curbs the cons in the existing retrieval techniques by reducing the semantic gap, with the help of combined low level and high level features. The resultant images are further optimized to perform effective retrieval.

III. PROPOSED APPROACH

This paper proposes a novel approach of content-based DICOM image retrieval accomplished by classification based multimodal image retrieval. It addresses the problem of retrieving query-by-example DICOM images from picture archiving and communication system (PACS). These images remain as an important source of functional and anatomical information for the diagnosis of diseases and medical research. Clinical decision support techniques such as case-based reasoning or evidence-based medicine can even produce a stronger need to retrieve images that can be valuable for supporting certain diagnoses.

However exact retrieval of the query image remains a challenging task due to vast amount of images stored in the database. A large number of retrieval methods have been implemented with the motto of providing efficient and effective multimodal image retrieval. But lots of limitations are posed with the retrieval methods.

The proposed method is a classification based multimodal image retrieval where the classification is done with respect to the features extracted.

The low level features, color and texture are extracted along with contour based segmentation, a high level feature, for all the images in the database. A visual feature database is constructed from the image database, using combined feature vector calculated from colour feature, obtained by colour moments, texture feature extracted from Gabor wavelet transform and shape feature, extracted by contour based segmentation into account. The global descriptors like area, circularity, eccentricity and major axis orientation are also extracted for the same.

A combined feature vector is generated from colour moments, gabor wavelet transform and contour based segmentation of the query image. Visual feature database construction is done offline, and feature vector for query image is constructed online. This avoids the delay in response time, in retrieving the relevant images. Vital and fast-computable features are chosen for feature vector, considering huge number of images present in the database.

Query image is mapped into a feature vector and the distance between the query and images in the database is calculated. The system ranks the whole dataset according to a minimum distance criterion. The distance is the sum of weighted Euclidean distances between pairs of feature vectors – feature vector of the database image and feature vector of the query image. The Weighted Euclidean Distance WED(X,Y) is calculated as follows:

$$WED\,(X,Y) = 1/S \,.\, \sum_{s=1} (X_s - Y_s)^2 .\, W_s k \qquad (1)$$

where, X,Y are feature vectors corresponding to the query image and the images in the database, S is the dimension of the feature vector, $W_s k$ is the weight associated with feature vector, k is the iteration number. If k=1, $W_s k = 1$ for all values of s.

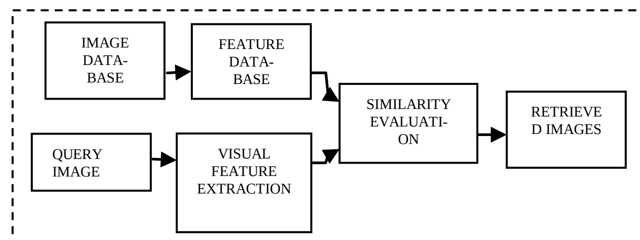

Fig. 1. Initial Image Retrieval

Based on the computed distance, the nearest images are retrieved from the database and are routed to classification.

The images are classified using neural networks. Here we consider three layers of neurons. The first layer has input neurons which send data via synapses to the second layer of neurons, and then via more synapses to the third layer of output neurons. The synapses store parameters are actually "weights" that manipulate the data in the calculations.

The next process is the clustering of the accumulated images into positive and negative feedback. The images are labelled as relevant or irrelevant, based on fuzzy c-means clustering.

Accordingly, relevant and irrelevant image subsets are created, which will be progressively populated across iterations, based on the change in weights of individual features, thus changing the distance between the query image and the database images.

This will help in retrieving the exact query image from the database. The RF based similarity technique is used, where in each iteration, the feature weights are updated.

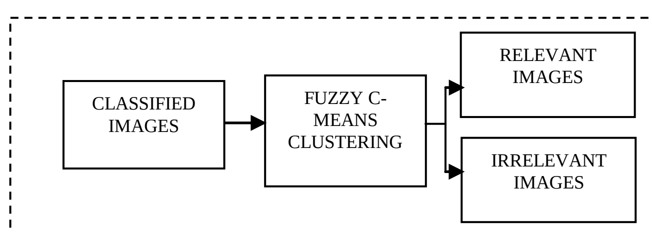

Fig. 2. Automatic Relevance Feedback

The feedback drives a feature re-weighting process. The feature reweighting process determines the importance of individual features in the retrieval process. Based on the reweighted feature value, the importance of each feature is set in the forth- coming iterations.

IV. EXPERIMENTAL SETUP AND RESULTS

For initial retrieval of images, 3000 multimodal DICOM images are used. The images are collected from various sources like computed tomography, magnetic resonance, digital radiography, radiation therapy and ultra sound. The experiment is implemented in jdk 1.6.42. The DICOM images are first converted into .jpg images, for effective processing.

After conversion, a combined feature vector is computed for every image, using, colour moments, Gabor wavelet transform and contour based segmentation. This feature vector is computed offline, so as to reduce the response time during retrieval. The pre-computed feature vectors are stored in a feature database.

Whenever new images are added to the database, the feature vector for the corresponding image is computed and stored in the feature database. This reduces the response time of retrieval to a great extent. The user is prompted with a screen to input the query image.

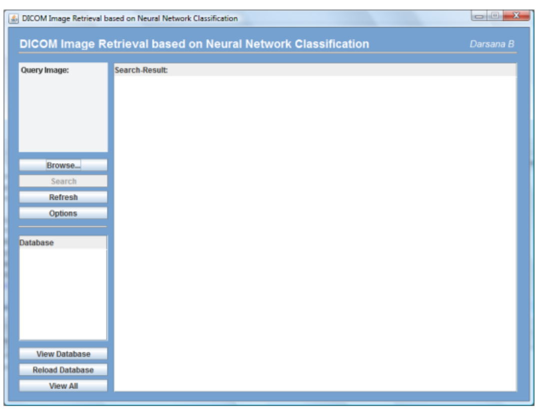

Fig. 3. DICOM Image Retrieval Applet

Here user inputs the query image, based on which, relevant images are retrieved in the resultant process. For the query image, a combined feature vector comprising of colour moments, gabor wavelet transform and contour based segmentation is constructed online. This feature vector is then compared with the feature vectors stored in the feature database.

The distance between the query feature vector, and the feature vectors in the feature database are computed using weighted Euclidean distance. The minimum the distance between the feature vectors, the images are more relevant. Based on this relevance the images are ranked, and first set of retrieved images results are obtained.

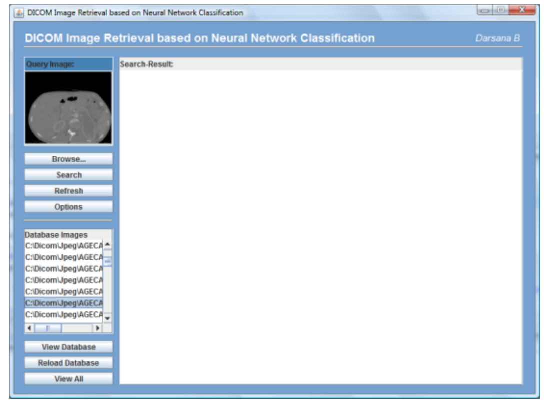

Fig. 4. Query Image Input

These images are further classified to obtain positive and negative relevance to achieve optimized retrieval.

The retrieved images are classified using three layer neural network. The weights of interconnections are updated in each iteration, for efficient retrieval. The images obtained are routed to fuzzy c-means clustering algorithm. The positive and negative relevance of every image with the query image is analyzed. Here the images are split into relevant images and irrelevant images, based on the positive and negative feedback output from the algorithm. The number of output images required can be controlled by the user. The user is prompted to enter the number of relevant results required.

Based on this, N number of most relevant images in the database is retrieved for any given query image. Once the resultant images are obtained, the end user can access the related information associated with the images. These attributes are very much helpful in case based reasoning, which aids in effective diagnosis of diseases from images, based on relevant examples.

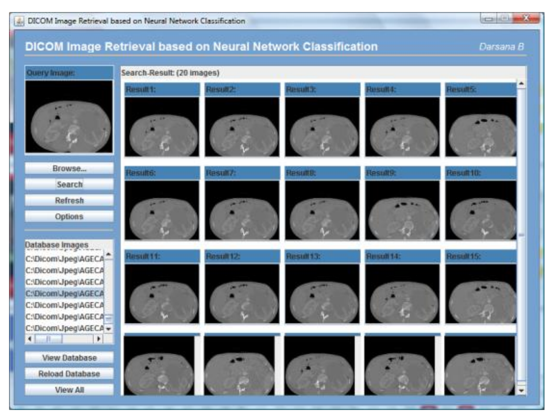

Fig. 5. Content-based DICOM image retrieval

Overall performance of the system is measured with precision and recall values obtained for query images. Precision is the fraction of the images retrieved that are relevant to the query image. Recall is the fraction of the images that are relevant to the query image which is successfully retrieved.

Multi-modal query images are chosen and are given as inputs for the retrieval. For every query image, the results are analyzed, and precision-recall values are computed. The obtained values are plotted. On average for the given query images, the precision value turns to be 0.78 and recall is 0.76. The following graph shows the precision-recall values for ten different query images.

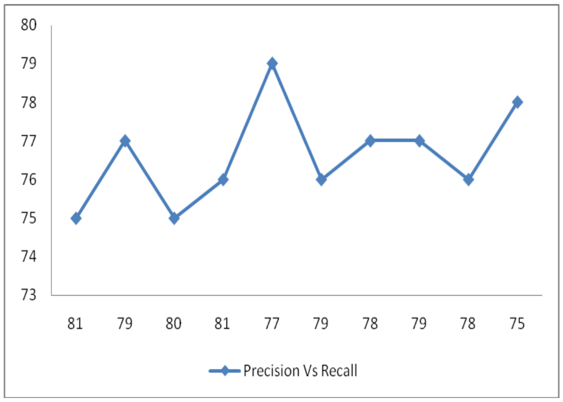

Fig. 6. Precision Vs Recall Graph

V. CONCLUSION

The initial Image Retrieval uses fast, easily computable, in-depth low-level and high-level features, which increases efficiency and reduces computational cost. Neural network classification emphasizes the most discriminating parameters. Relevant image retrieval problem is formulated as an optimization problem, and is solved using fuzzy c-means algorithm.

It takes into account the characteristics of relevant and irrelevant images, as points of attraction and repulsion, thus performing an effective retrieval. The proposed approach achieves the following goals without any human interaction – clustering relevant images using meta-heuristics and dynamically modifies the feature space by feeding automatic relevance feedback. The result thus obtained will be very much supportive in case-based reasoning and evidence-based medicine.

REFERENCES

[1] Song Yan, “Research of Image Retrieval Based on color and texture feature”, *Computer application and soft computing*, 2007, 9(2), pp. 42-50.

[2] Ye Yu-guang, “Research of image retrieval based on fusing with multi-character*”, Hua Qiao university*, 2007, pp.14-36.

[3] Wang, David Zhang, and Hongzhi Zhang, “Combination of Polar Edge Detection and Active Contour Model for Automated Tongue Segmentation”, In Proceedings of the *Third International Conference on Image and Graphics*, pp: 270-273, 2004.

[4] Sameer Antani, L. Rodney Long, George R. Thoma, "Content-Based Image Retrieval for Large Biomedical Image Archives", *MEDINFO*, Amsterdam, 2004.

[5] Henning Muller, Nicolas Michoux, David Bandon and Antoine Geissbuhler, "A review of content-based image retrieval systems in medical applications——clinical benefits and future directions", *International Journal of Medical Informatics*, Vol.73, pp. 1-23, 2004.

[6] R. Senthil Kumar, Dr. M. Senthilmurugan, “Content-based Image Retrieval System in Medical Applications”, *International Journal of Engineering Research & Technology(IJERT)*, Vol. 2 Issue 3, March 2013.

[7] Piyamas Suapang and Surapun Yimmun ,"Dicom-Format Image Archiving, Medical Images Compression And Web-Based Integrated Medical Information System", in Proc. of The *Third Biomedical Engineering International Conference*, pp. 260-264, 2010.

[8] N. Umadevi and Dr.S.N. Geethalakshmi, "Improved Hybrid Model For Denoising Poisson Corrupted Xray Images", *International Journal on Computer Science and Engineering*, Vol. 3 , No.7,Jul2011.

[9] Abolfazl Lakdashti and Hossein Ajorloo ,"Content-Based Image Retrieval Based on Relevance Feedback and Reinforcement Learning for Medical Images",*ETRI Journal*, Vol.33, No. 2, 2011.

[10] Haiwei Pan and Xiaolei Tan Qilong Han Guisheng Yin ,"A Domain Knowledge Based Approach forMedical Image Retrieval", I.J. *Information Engineering and Electronic Business*,Vol.3, pp.16-22, 2011,

[11] J. R. Smith and S.-F. Chang, "VisualSEEk: A Fully Automated Content-Based Image Query System," Proc. the *Fourth ACM International Conference on Multimedia '96*, Boston, MA, 1996.

[12] MeCastillo, Carlos D. Barranco, Juan Miguel Medina, Sergio Jai and Jesus R. Campana ,"On the Use of a Fuzzy Object-Relational Database for Flexible Retrieval of Medical Images", *IEEE Transactions On Fuzzy Systems*, Vol. 20, No. 4,2012.

[13] B. Ramamurthy and K.R. Chandran ,"Content based Image Retrieval for Medical Images using Canny Edge Detection Algorithm", *International Journal of Computer Applications*,Vol.17, No.6,pp. 0975–8887,2011

[14] Ramamurthy, B. and K.R. Chandran ,"Content Based Medical Image Retrieval with Texture Content Using Gray Level Co-occurrence Matrix and K-Means Clustering Algorithms", *Journal of Computer Science*, Vol. 8, No.7,pp. 1070-1076, 2012.

[15] B. Jyothi, Y. Madhavee Latha, P.G. Krishna Mohan and V.S.K. Reddy ,"Medical Image Retrieval Using

Moments", *International Journal of Application or Innovation in Engineering & Management*, Vol. 2, No. 1, 2013

[16] MeCastillo, Carlos D. Barranco, Juan Miguel Medina, Sergio Jai and Jesus R. Campana, "On the Use of a Fuzzy Object-Relational Database for Flexible Retrieval of Medical Images", *IEEE Transactions on Fuzzy Systems*, Vol. 20, No. 4, 2012.