Available Online at www.ijcsmc.com

International Journal of Computer Science and Mobile Computing

A Monthly Journal of Computer Science and Information Technology

ISSN 2320–088X

IJCSMC, Vol. 4, Issue. 11, November 2015, pg.256 – 266

RESEARCH ARTICLE

A MEDICAL IMAGE RETRIEVAL SYSTEM USING HYBRID FOCS FRAMEWORK

Suresh R[1], PG Scholar in Department of Computer Science and Engineering (with spln in Networks), Regional Centre of Anna University, Coimbatore, Tamil Nadu, India

Newlin Rajkumar M[2], Assistant Professor, Department of Computer Science and Engineering, Regional Centre of Anna University, Coimbatore, Tamil Nadu, India

[1] rsuresh.breeze@gmail.com, [2] newlin_rajkumar@yahoo.co.in

Abstract-The proposed system uses a hybrid approach for the retrieval of medical diseases from MRI images is introduced. The main objective of this work is to retrieve the brain images from huge volume of medical image database with high accuracy by performing Feature Extraction, Feature Optimization, Feature Classification, and Similarity Measurement. This type of Content Based Medical Image Retrieval (CBMIR) is called Feature Optimized Classification Similarity (FOCS) framework.

For a given brain query image, extract Texture Features using Gray Level Co-occurrence Matrix (GLCM) and Tamura Features. The optimized feature selection is done by Fuzzy adaptive Particle Swarm Optimization (FPSO) Technique. Based on the extracted features, the image classification process is applied to identify the relevant class of features and irrelevant class of features using Relevance Vector Machine (RVM) which yields an optimum solution with few training samples. The Euclidean Distance (ED) is used to find the similarity between the query image and database images. The retrieval algorithm performances are estimated in terms of precision and recall. This proposed framework is used to help the physician to obtain more confidence in their decisions for diagnosis and medical research students are passion to get the essential images successfully for further investigation of their research.

Keywords— patches, sparse

I. INTRODUCTION

1.1 OVERVIEW

As more and more hospitals switch to a complete IT-based management of patient data, e.g., by using Electronic Health Records (EHR), huge amounts of medical information has to be stored and made accessible using computer technology. The nature of this data is diverse in more than one aspect. Imaging systems and image archives have often been described as an important economic and clinical factor in the hospital environment. Medical imaging field has been developed to produce more attractive techniques to analyze the medical images to physicians for immediate diagnosis and to the medical research students for further analysis of their research. Many imaging modalities, such as Computed Tomography (CT), Magnetic Resonance (MR), Ultrasound (US), Mammograms (MG), and Digital Radiography (DR),are presently existing which would be used to convey the desired images to physicians at precise time to diagnose and to give treatment for that specific diseases and for medical research students to have a further analysis of their research such as finding the commonness of a obsessive feature in a large survey collection. It would not be possible to access or make use of those particular images unless it is arranged in a structured manner. Medical image retrieval system plays a vital role that would locate a desired image from a large varied collection of image database.

1.2 CONTENT BASED MEDICAL IMAGE RETRIEVAL

The radiology department of hospitals is well established with Picture Archiving and Communications Systems (PACS) [10] in which image storage, retrieval and transfer of images are performed using the format of DICOM (Digital Imaging and Communications in Medicine). The search of image is carried out based on the textual features of image headers such as patient id, name and other technical parameters such as image modality, body parts, orientations etc,. There have been testified errors in the exactness of DICOM headings. Often the radiology department is not entering a proper or adequate data into systems also pool of image contents are not clearly described by text. Content Based Medical Image Retrieval System (CBMIR) is developed to make automatic indexing by extracting the content of visual features by using low level features such as texture, shape, color etc., to provide adequate information. Such mechanism is called as Query by image Example which requires a set of descriptive features and some similarity metrics to compare the query image with database image.

1.2.1 MRI Medical Image

There are lot of research has made to retrieve brain images from MRI brain image database. Brain is an important organ since it plays a vital role in human organ system. Therefore, Brain diseases have attracted much attention for a long time. Diagnostic MRI is a useful clinical tool for visualizing organs and soft tissues in human skull without any deteriorating effects. It enables the physician to select the right image plane to display pathological anatomy accurately. Its significance is that it is safe to handle, non-radiological and non-invasive. Brain diseases are best identified using these gray scale images. Traditionally, to determine whether the brain tissue is normal or abnormal relies on specialized radiologists. The decisions made radiologist are heavily dependent on their experience, which might be related to certain characteristics from the visual interpretation of the image or some comparisons with different pathologies [2].

The advantages of Magnetic Resonance Imaging are that the spatial resolution is high and provides detailed images. Magnetic Resonance Images are used in detecting and tracking brain tumors. The tracking of the tumors is important especially when a patient is under medication in order to observe the changes that appear. Diagnostic brain MRI scans are usually performed by trained medical technologists who manually prescribe the position and orientation of a scanning volume. In this study, a fully automatic computer algorithm is described which compensates for variable patient positioning and acquires brain MRI scans in a predefined reference orientation. The human brain is among the most complex systems known to man. The rapidly growing technology in the past decade has made it possible for physicians to capture simultaneous responses from brain functions to test many long-standing brain theories. Almost all experiments in brain research have resulted in massive amounts of data. Often, neuroimaging and neurophysiological signals come in the form of large spatial and temporal data, also known as Multidimensional Time Series (MDTS). Very few studies in brain research and data mining have been tailored to exploit both spatial and temporal properties of these brain data. The exploration of such massive medical data requires very efficient and sophisticated techniques capable of capturing both spatial and temporal properties simultaneously. The method involves acquiring a rapid water-only pilot scan, segmenting the brain surface, and matching it to a reference surface. Usually a brain MRI procedure includes T1weighted, T2weighted and FLAIR sequence in two or three planes:

1. **T1-weighted** scans use a Gradient Echo (GRE) sequence, with short echo time(TE) and short repetition time (TR).
2. **T2-weighted** scans use a Spin Echo (SE) sequence, with long TE and long TR. Echo time (TE) and the repetition time (TR).
3. Fluid Attenuated Inversion Recovery (**FLAIR**) is an inversion-recovery pulse sequence used to null signal from fluids.

The CBMIR problem is a challenging topic of current research and is of growing interest in medical applications such as medical records systems. The ability to use non-text information to search for images having certain characteristics would add a powerful new dimension to medical imagery. For large image databases, practical CBIR methods must be very fast and efficient in their query and retrieval operations. To help achieve this, concentrates upon extracting useful features and indexing them for efficient search.

II. LITERATURE REVIEW

Brain is an important organ since it plays a vital role in human organ system. Therefore, Brain diseases have attracted much attention for a long time. Diagnostic ultrasound is a useful clinical tool for visualizing organs and soft tissues in human abdominal wall without any deteriorating effects. It enables the physician to select the right image plane to display pathological anatomy accurately. Its significance is that it is safe to handle, non-radiological and non-invasive. One such application of diagnostic ultrasound is Brain imaging. Brain diseases are best identified using these gray scale images. Traditionally, to determine whether the Brain tissue is normal or abnormal relies on specialized radiologists. The decisions made by radiologist are heavily dependent on their experience, which might be related to certain characteristics from the visual interpretation of the image or some comparisons with different pathologies [10]. However, several studies have shown the accurate decision rate by using simple visual interpretation of Brain diseases is only about 54%.

The main use of this project is helping the doctors in diagnostic aid. Several solved cases can be saved in Content Based Medical Image Retrieval systems with patient data and diagnosis so that when the same case will appear in Future that be diagnosed in less time. The indexing and retrieval should be so fast so that doctors will not spend their precious time in solving one case.

Image representation scheme designed for medical image retrieval systems can be categorized into two classes:

1) Keyword (text) Features,
2) Visual Features

2.1 Keyword Based Medical Image Retrieval

Image Retrieval (IR) based on keyword features can be traced back to the late 1970's, mainly developed by database management and information retrieval community. The typical query scenario in such IR systems is Query By Keyword (QBK). Semantics of images can be accurately represented by keywords, as long as keyword annotations are accurate and complete. The challenge is that when the size of image database is large, manual annotation becomes a tedious and expensive process. Although it is possible to use surrounding text of images on the Web to extract keyword features of the images, such automatically extracted keywords are far from being of images for the users to label. These facts limit the scale up of keyword-based image retrieval approaches.

2.2 Visual Feature Based Medical Image Retrieval

Content Based Image Retrieval (CBIR) was proposed to overcome the difficulty of manual annotations. It is a process to find images similar in visual content to a given query from an image database. It is usually performed based on a comparison of low level features such as color, texture, or shape features, extracted from the image themselves. The typical query scenario in such image retrieval system is Query By image Example (QBE). While there is much research effort addressing CBIR methods are still limited, especially in the two aspects of retrieval accuracy and response time.

The limited retrieval accuracy is because of the big gap between semantic concepts and low-level image features, which is the biggest problem in CBIR. For example, for different queries, different types of features have different significance; an issue is how to derive a weighting scheme to balance the relative importance of different feature type and there is no universal formula for all queries. The slow response time is because of high dimensionality of the feature space, typically hundreds to thousands.

CBMIR is an active research area, however, it has not made substantial progress when unified into an application of healthcare and medical research due to the following gaps [5] represented in Table 1:

Table 2.1: CBMIR Gaps

Gaps	Description
Content Gap	Context. Semantic and Diagnostic protocols
Feature Gap	Feature Extraction, Scale, Dimension
Performance Gap	System implementation, Acceptance, Availability, Integration, Feature Indexing and Evaluation
Usability Gap	Query features integration, Query refinement

Researchers are seeking to overcome the above gaps to make CBMIR as a highly efficient system [6].The following some of the existing CBMIR systems are used to retrieve required images from the medical image databases for the purpose of radiologists to take clinically proven decision support and for the purpose of medical student research education.

There was a lot of work in the last years for the construction of CBMIR systems and represented in Table.

Table 2.2: CBMIR SYSTEM

CBMIR	**Images used**	**Visual Features**
ASSERT (Automatic Search and Selection Engine with Retrieval Tools)[9]	High-Resolution Computed Tomography (HRCT) of lung	Texture, Shape, Edges, and Gray-scale Properties
CasImage[4]	A variety of images from CT, MRI, and radiographs, to color photos	Global and Regional Color and Texture features
IRMA (Image Retrieval in Medical Applications)[8]	Various imaging modalities	Global and Local Shape and Texture Features
NHANES II (The Second National Health And Nutrition Examination Survey)[6]	cervical and lumbar spine X-ray image	Shape Features
Image Map[1]	Multiple Images of organs	Individual Regions and Spatial Relationships between Regions of Shape and Texture Features
MIMS Medical Image Management System [2]	X ray ,CTs of the Head Images	Text and Shape Features
Plaque CBIR system[3]	Plaque Images	Shape and Texture Features

Medical image categorization, registration, feature extraction, Classification indexing and retrieval is performed over the entire image database in the above mentioned Image Retrieval Systems. Each method has its own advantages and disadvantages in their retrieval performance.

Different authors has used different image features set and image classification methodology for their medical image retrieval applications.

Successful CBMIR applications can be developed by choosing an efficient algorithm at several stages of indexing and retrieval workflow. The goal of our work is to develop an efficient medical image retrieval system that gears recent developments in the following phases:

- Phase I: Visual Feature Extraction
- Phase II: Optimized Feature Selection
- Phase III: Classification of Features
- Phase IV: Similarity measurements

Phase I Visual Feature Extraction: Feature extraction [1] is the base for image retrieval. Within the visual feature scope, the features can be further classified as general features and domain specific features. The former include color, texture, and shape features while the latter is application-dependent and may include, for example, human faces and finger prints. General visual features such as Shape and Texture are most widely used in CBMIR [2].

Texture Features: Texture refers to visual patterns with properties of Homogeneity and consists of basic primitives (texels or micro patterns) whose spatial distribution in the image creates the appearance of a texture. There are two basic classes of texture descriptors, namely, statistical model-based and transform-based. The former one explores the grey-level spatial dependence of textures such as Gray Level Co-occurrence Matrix and tamura features extracts some statistical features as texture representation. The latter approach is based on spatial frequency and Transform Domain Features such as Gabor Filter Features and Wavelet Features.

Shape Features: Shape is an important feature for medical image retrieval. There are two types of approaches used in shape representation. One is the contour based shape method and the other one is the region based method. Contour shape techniques only exploit shape boundary information and Region based methods consider all the pixels within a shape region. The contour based shape method can be represented by moment invariants, Generic Fourier descriptors, chain code, eccentricity, Shape signature etc., The region based shape method can be represented as Zernike Moments, Grid Method, Shape Matrix, Convex Hull etc.,

2.3 Medical Image Feature Selection

The extracted image features are formed as Feature Vector Database. Feature selection can be defined as selecting the amalgamation of describes a particular feature set is best. The feature selection is a widespread research topic since 1970's in pattern recognition, image retrieval and numerous research fields. The greater the feature dimensionality in CBMIR results in lower the performance of feature classification generates problems in constructing efficient data structures for search and retrieval. Mostly, the indexing structures could not balance well when the dimensionality of the feature vector outstrips 20. An extraneous and redundant feature is eliminated by using dimensionality reduction techniques[3] and extracts a small number of appropriate features. The intrinsic dimensionality is required to represent the image feature values. Due to this reason, there is an extensive interest in reducing the dimensionality of the descriptors while stabilizing the unique topology of the high dimensional space. Earlier investigation procedures for dimensionality reduction includes Principal Component Analysis [4], Weighted Multi-Dimensional Scaling [5], Tabu Search Method [6]. For the past several years Evolutionary Algorithm (EA) operates on a population of possible solutions by relating the principle of presence of the fittest to yield better and better estimates to a solution. The key inspiration for using EAs is to search a set of possible solutions simultaneously to find the optimal feature selection with a least runs of algorithm. The mainly used EAs for optimizing the feature selection are Particle Swarm Optimization(PSO) [1],Genetic Algorithms, Gravitational Search algorithm [2] Ant Colony Optimization(ACO), Anna Veronica Baterina. The comparison of various optimization techniques [3] are performed for nonlinear mapping and large datasets for neural networks.

2.4 Medical Image Feature Classification

The feature vectors optimized in different points of a texture images are not identical. Training the classification systems with these optimized features could raise the accuracy rate. Image classification [4] is performed in which optimized features are given as input to the image classification tool in order to classify the images. Mathematical process whereby elements of image data sets are categorized into a limited number of separable, discrete classes:

1) Train the classification-system on the Optimized feature set associated with the classes of interest.

2) Using classification decision rule, the classification-system decides which class each optimized features pixel most looks like the features.

The most widely used classification algorithms[5] are K-nearest neighbour, Fuzzy C-Means clustering, Decision Tree, Bayesian Classification etc., some of the interesting machine learning algorithms are facilitated to classify medical images and to enhance the information by using Support Vector Machine Relevance Vector Machine, Kernel Fisher Discriminant Analysis etc., The solitary approach in each stage of four phases are seek to focus on to identify the potential optimal solutions within a reasonable amount of time .A hybrid approach is required to build an efficient retrieval system in each stages, which subsequently search the solutions space quickly by considering the proper choice of methodologies, parameters in which convergence speed is raised to get an optimal fact in each of the four phases of medical image retrieval system.

To search for a particular image for immediate medical diagnosis in the field of medical domain and effective treatments for the Physicians or Radiologists .

- To get the essential images successfully for a medical research students and teaching institutions, are keen for further analysis of their research.
- This system is very efficient in hospitals for easy retrieval of medical images and diagnosis the result and Storage of medical images
- Flexible query methods: flexibility to handle complex queries combining several image attributes.

2.5 Similarity Measurements

Similarity measurement is the main tool for retrieving similar images from the classified image feature vector databases. Several similarity measurement distance metrics such as Manhattan Distance (L1 metric), Euclidean Distance (L2 metric), Vector Cosine Angle Distance (VCAD), Chord Distance, Pearson's Correlation Coefficient, Spearman Rank Coefficient [5]. have been proposed in the literature for measuring similarity between feature vectors. An effective retrieval system is based on choosing the similarity measure that selects the suitable classified reference samples of the same class between the query image and the database images.

The solitary approach in each stage of four phases is to focus on to identify the potential optimal solutions within a reasonable amount of time .A hybrid approach is required to build an efficient CBMIR which would searches the solutions space quickly by choosing the efficient methods and parameters in which convergence speed is raised to get an optimal fact in each of the four phases.

III. EXISTING SYSTEM

3.1 Introduction

In keyword feature based image retrieval systems, semantics of images are accurately specified but vast amount of labor required in manual image annotations. In visual feature based image retrieval systems, images would be indexed by their own visual content, such as color, shape, texture. CBMIR systems are currently being integrated with PACS for increasing the overall search capabilities and tools available to radiologists [9].

3.2 Keyword Features

Image Retrieval (IR) based on keyword features can be traced back to the late 1970’s, mainly developed by database management and information retrieval community. The typical query scenario in such IR systems is Query By Keyword (QBK). Semantics of images can be accurately represented by keywords, as long as keyword annotations are accurate and complete. The challenge is that when the size of image database is large, manual annotation becomes a tedious and expensive process. Although it is possible to use surrounding text of images on the Web to extract keyword features of the images, such automatically extracted keywords are far from being of images for the users to label. These facts limit the scale up of keyword-based image retrieval approaches.

3.3 Visual Features

Content Based Image Retrieval (CBIR) was proposed to overcome the difficulty of manual annotations. It is a process to find images similar in visual content to a given query from an image database. It is usually performed based on a comparison of low level features such as color, texture, or shape features, extracted from the image themselves[9]. The typical query scenario in such image retrieval system is Query By image Example (QBE). While there is much research effort addressing CBIR methods are still limited, especially in the two aspects of retrieval accuracy and response time.

The limited retrieval accuracy is because of the big gap between semantic concepts and low-level image features, which is the biggest problem in CBIR. For example, for different queries, different types of features have different significance; an issue is how to derive a weighting scheme to balance the relative importance of different feature type and there is no universal formula for all queries. The slow response time is because of high dimensionality of the feature space, typically hundreds to thousands.

3.4 Relevance Feedback

While it is a long-term effort to improve the semantic representation power of visual features, an effective approach is to incorporate relevance feedback process and learning techniques, online and offline, to learn better representations of images and/or refine queries[7]. Relevance Feedback (RF), originally developed for information retrieval, is an online learning technique used to improve the effectiveness of information retrieval systems. Since its introduction into image retrieval, it has been shown to provide dramatic performance improvement. It is expected to maximize the ratio between the quality of the retrieval results and the amount of interaction between the user and the system.

The main idea of relevance feedback is to let users guide the system. For a given query, the CBIR system first retrieves a list of ranked images according to a predefined similarity metrics, often defined by the distance between query vector and feature vectors of images in a database. Then, the user selects a set of positive and/0r negative examples from the retrieved images, and the system will refine the query and retrieve a new list of images. Hence, the key issue in relevance feedback approaches is how to incorporate positive and negative examples in query and/or the similarity refinement.

Although relevance feedback can significantly improve the retrieval performance, its applicability still suffers from three inherent drawbacks [8].

(a) **Incapability of capturing semantics.** Most RF techniques in CBIR absolutely copy ideas from textural information retrieval. They simply replace keywords with low-level features and then adopt the vector model for document retrieval to perform interactions. This strategy works well underlying the premise that the low-level features are as powerful in representing the semantic content of images, as keywords in representing textural information. Unfortunately, this requirement is often not satisfied. Therefore, it is difficult to capture high-level semantics of images when only low-level features are used in RF.

(b) **Scarcity and imbalance of feedback examples.** Very few users are willing to go through endless iterations of feedback with the hopes of getting the best results. Hence, the number of feedback examples labeled by users during a RF session is far smaller than the dimension of low-level features that characterize an image. Because of such small training data sizes, many classical learning algorithms cannot give exciting results [7]. Furthermore, in the RF scenario, the number of labeled negative examples is usually greater than the number of labeled positive examples. The imbalance of training data always makes classification learning less reliable. Thus, the scarcity of feedback examples, especially positive examples, definitely limits the accuracy of RF.

(c) **Lack of the memory mechanism.** A disadvantage of the traditional RF is that the potentially obtained semantic knowledge in the feedback processes of one query session is not memorized to continuously improve the retrieval performance. Even with the same query, a user will have to go through the same, often tedious; feedback process to get the same result, despite the fact the user has given the same query and feedbacks before. Hence, there is an urgent need of building a memory mechanism to accumulate and learn the semantic information provided by past user interactions.

The proposed system uses the following procedures to solve the difficulties in the relevance feedback process.

(a) By forming a semantic network on top of the keyword association on the images, it is able to accurately deduce and utilize the images semantic contents for retrieval purposes.
(b) The semantics and low-level feature based relevance feedbacks are combined to help each other in achieving higher retrieval accuracy with lesser number of feedback iterations required from the user.
(c) Once the user is done with a query and starts a new query, the knowledge gained by the systems with previous queries are not lost because of learning strategy used in relevance feedback.

IV. PROBLEM DEFINITION

- Feature Extraction Problem:
  - Imprecise understanding of visual feature representation is due to the gap between the visual features and semantic concepts of image.
  - Specific Feature Extraction degrades the performance of CBMIR.
- Feature Selection Problem:
  - The greater the feature dimensionality in CBMIR, it results in lowering the performance of feature classification that generates problems in constructing efficient data structures for search and retrieval.
  - The individual feature selection approach is to focus on identifying the potential optimal solutions within a reasonable amount of time which in turn make the system have an impulsive convergence in which comprehensive optimal fact and the convergence speed is decreased
- Feature Classification Problem :
  - Mostly all feature training points are taken uniformly during the training but in many real world applications, the inspirations of the training points are different.

V. SAMPLE OUTPUT

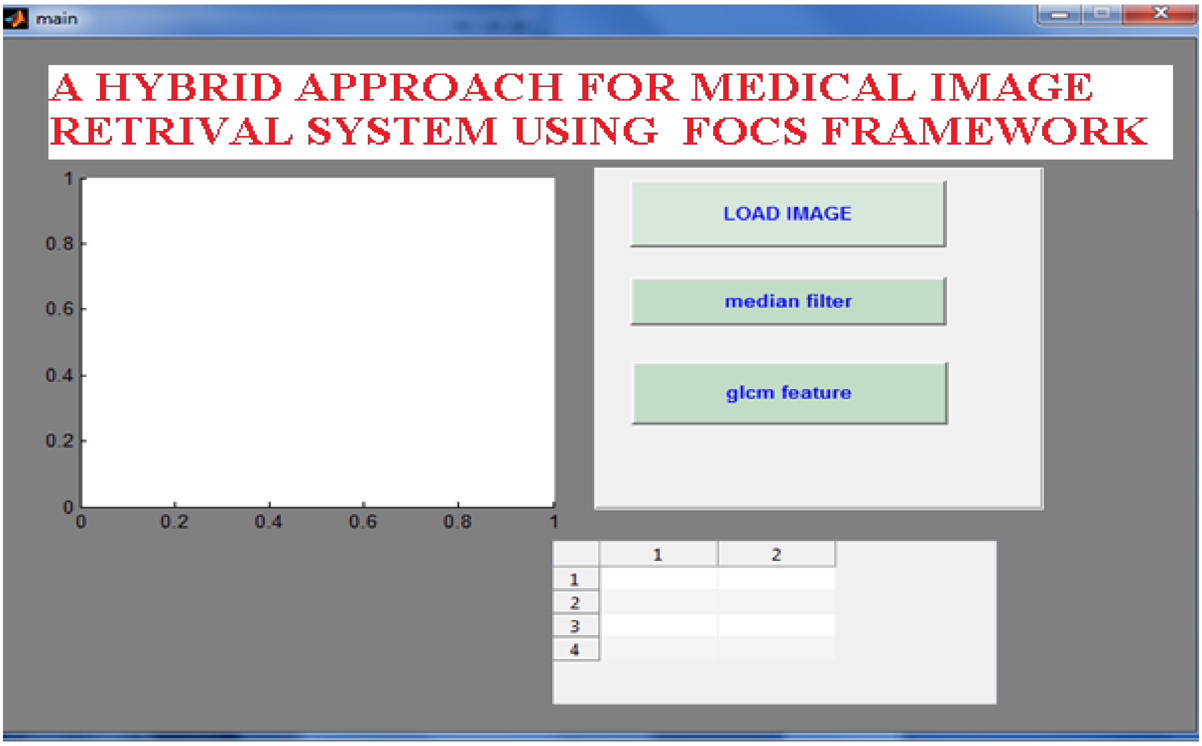

Fig 5.1 Main Form

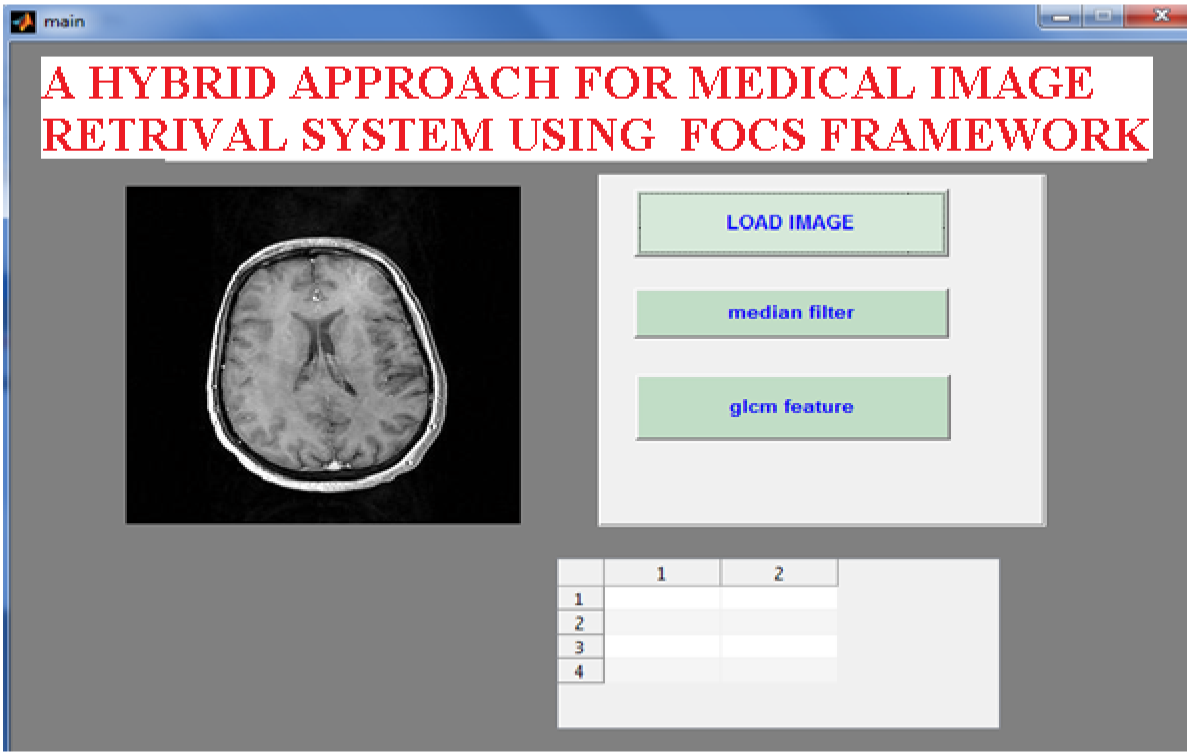

Fig 5.2 load image

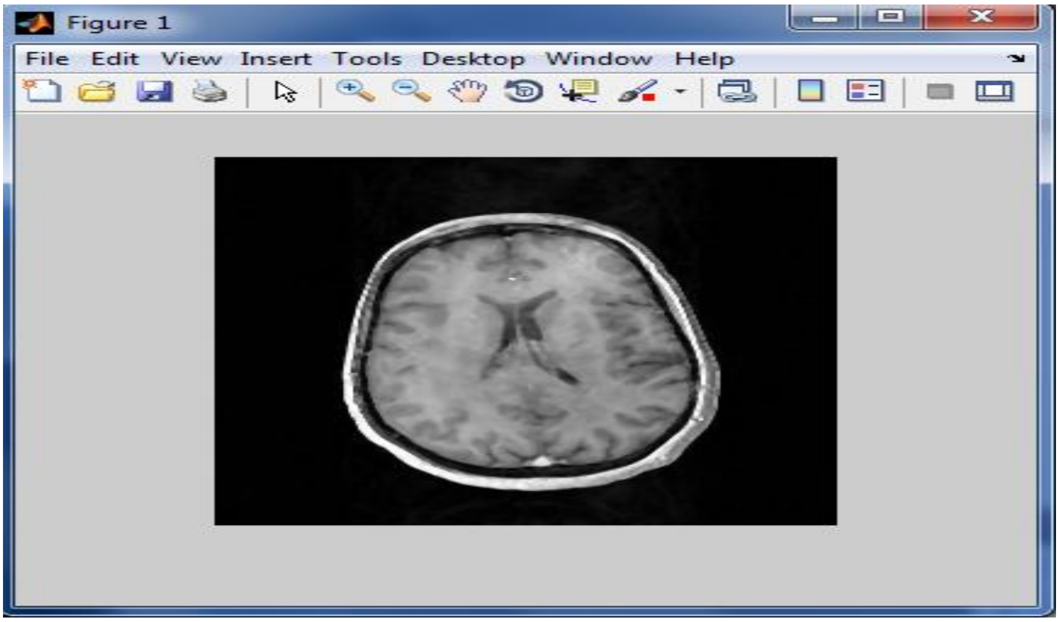

Fig 5.3 Median filtering the image

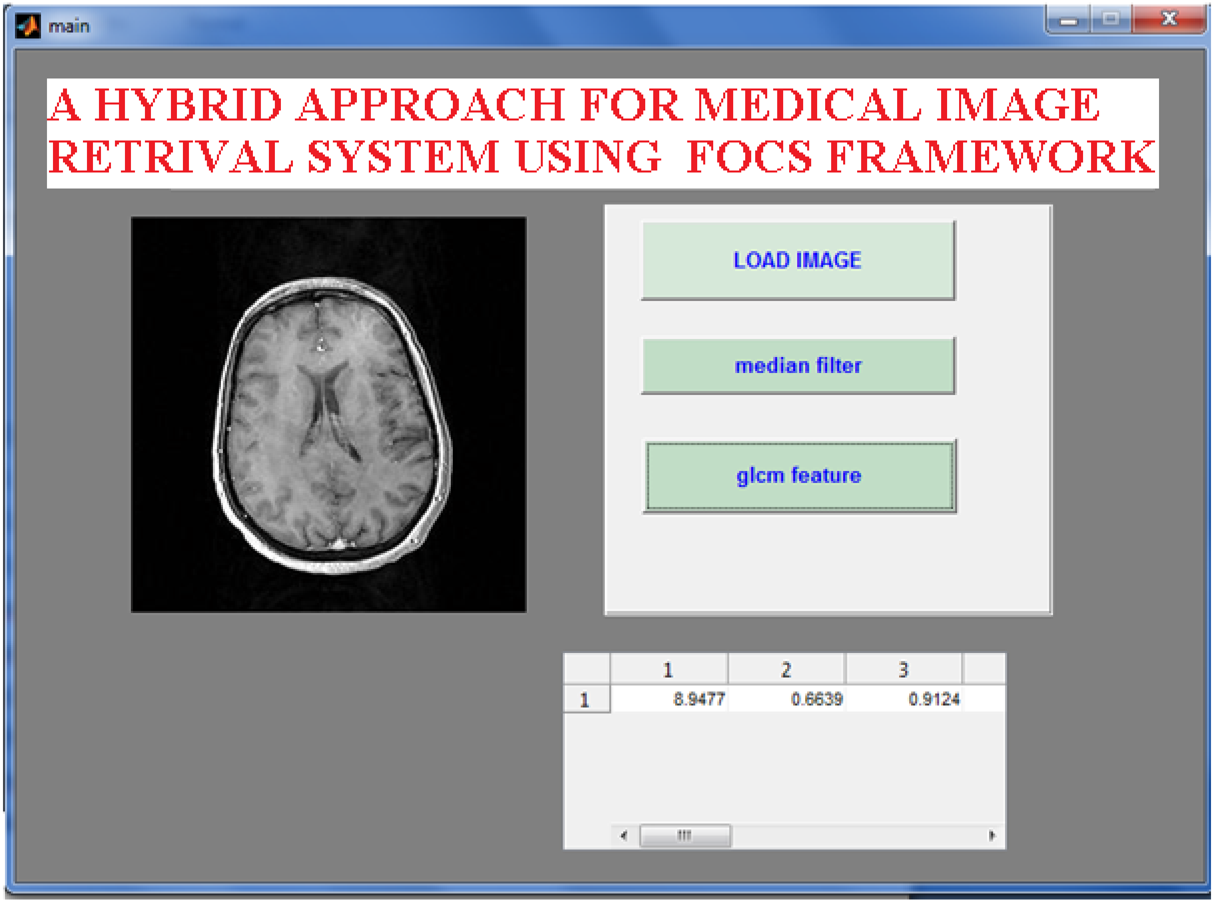

Fig 5.4 Extracting the GLCM feature

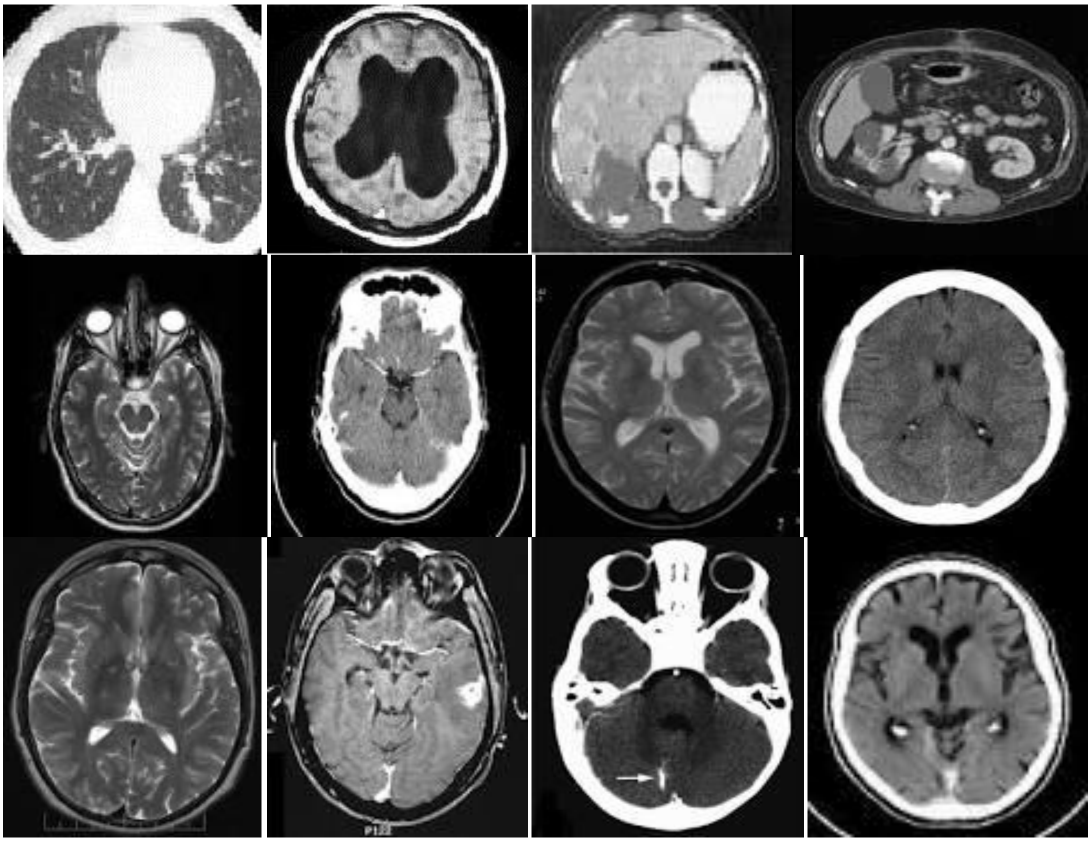

Fig 5.5 Sample Images

Table 5.1 Sample GLCM features

Image	contrast	correlation	cluster prominence	cluster shade	dissimilarity	energy
Brain1.jpg	0.73394	0.956513	2187.895829	168.3935901	0.228531	0.43915
Brain2.jpg	0.77461	0.950686	1880.615718	146.8397647	0.24926181	0.42864
Brain3.jpg	0.87992	0.943365	1756.877713	136.5579012	0.26494833	0.42612
Brain4.jpg	0.77928	0.922675	868.1222081	80.21498339	0.23093012	0.43957
Brain5.jpg	0.78162	0.919226	800.8243098	75.94220218	0.2296998	0.44351
Brain6.jpg	0.7794	0.921993	806.4190841	76.88712769	0.23025344	0.44926
Brain7.jpg	0.77694	0.919279	782.3653419	75.5399495	0.22883858	0.45133
Brain8.jpg	0.77802	0.922095	815.6312406	78.75835493	0.22314838	0.45946
Brain9.jpg	0.75464	0.923436	818.7360304	79.51325545	0.21822712	0.46261
Brain10.jpg	0.73868	0.923405	822.3533325	80.66330782	0.20761565	0.47111

VI. CONCLUSION AND FUTURE ENHANCEMENT

6.1 Conclusion

The above mentioned gap is avoided by developing a framework for effective medical image retrieval by integrating visual features using optimization, classification and similarity measurements techniques. Successful CBMIR applications can be developed by choosing an efficient algorithm at several stages of indexing and retrieval workflow. The proposed system is represented in Figure 1.The goal of the proposed work is to develop an efficient medical image retrieval system that gears recent developments in the following phases:

1) Phase I: Visual Feature Extraction
2) Phase II: Optimized Feature Selection
3) Phase III: Classification of Features
4) Phase IV: Similarity measurements

1) **Medical Image** as given as Input to the system.
2) For a given query image, **extract Texture Features** using **GLCM, Tamura features**
3) The optimized feature selection is done by using a **Fuzzy adaptive algorithm is integrated with particle swarm optimization (PSO).**
4) Based on the optimized features, **the image classification process** is applied to identify the relevant class of features and irrelevant class of features. **Relevance vector machine (RVM)** is used for data classification which yields an optimum solution with few training samples**.**
5) Finally searching and retrieval process is performed using well known Similarity Measurement as Euclidean Distance(ED)

6.2 Future Enhancements

Content based image retrieval system is using the existing inbuilt function of java software is easiest way to implement. It is not necessary that image having same color is of same domain, so there is a need of comparing texture and shape also to improve results. As image collections grow in size the system may take a lot of time, and eventually reduce the query-retrieval process. To increase the speed and the user's interaction with image retrieval systems, the images to be access from the web/Internet sources and the CBIR system can be implemented over the World Wide Web and applying proposed Fuzzy-PSO algorithm in a more efficient manner.

REFERENCES

1. A Review of Content-Based Image Retrieval Systems in Medica,Applications-Clinical Bene_ts and Future DirectionsHenning M□uller, Nicolas Michoux, David Bandon and Antoine Geissbuhler Division for Medical Informatics, University Hospital of Geneva Rue Micheli-du-Crest 21, 1211 Geneva 14, Switzerland.
2. A. Guimond and G. Subsol, “Automatic MRI database exploration and applications,” Pattern Recogn. Artif. Intell., vol. 11, no. 8, pp. 1345–1365, 1997.
3. Chaur-Chin Chen and Hsueh-Ting Chu,2005. Similarity Measurement between Images, Proceedings of the International Conference on Computer Software and Applications, July 26-28,IEEE Xplore,USA ,pp:41 – 42.DOI:10.1109/COMPSAC.2005.140.
4. Chris ding, Xiaofeng he,2004.K-means Clustering via Principal Component Analysis. Proceedings of the International Conference on Machine Learning,July 4-8,ACM New York,USA,pp:225-232.ISBN:1-58113-838- DOI :10.1145/1015330.1015408
5. Combined DICOM and HL7 viewer insupport of a bridge from content-basedimage retrieval to computer-aided diagnosis Petra Welter, Fatih Topal, Sebastian Jansen, Thomas M. Deserno, J¨org Riesmeier, Christoph Grouls, Rolf W. G¨unther
6. Hongbin Zhang, Guangyu Sun,2002.Feature selection using tabu search method, Journal of Pattern Recognition Society, 35 (2002) 701-711.Published by Elsevier Science Ltd, 0031-3203/01/ PII: S 0 0 3 1 - 3 2 0 3 (0 1) 0 0 0 4 6 – 2.
7. P. M. Kelly and T. M. Cannon, “CANDID: comparison algorithm for navigating digital image databases,” in Proc. Int. Working Conf. Scientific and Statistical Database Management, 1994, pp. 252–258.
8. Thomas Deselaers, Daniel Keysers, Hermann Ney,2008. Features for image retrieval: an experimental Comparison. Journal of Information Retrieval, Springer Science, pp:77-107.DOI:10.1007/s10791-007-9039-3.
9. Y. Rui and T. Huang, “Image retrieval: current techniques, promising directions and open issues,” J. Visual Commun. Image Representation, vol. 10, pp. 39–62, 1999.
10. Yogapriya J. Dr.Ila.Vennila, 2012. Medical Image Retrieval System using GGRE Framework.Proceedings of the International Conference on Pattern Recognition, Informatics and Medical Engineering ,March 21-23, IEEE Xplore Press,India,pp:246-251. DOI: 10.1109/ICPRIME.2012.6208352.