A Hybrid Approach Based Medical Image Retrieval System Using Feature Optimized Classification Similarity Framework

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ABSTRACT

For the past few years, massive upgradation is obtained in the pasture of Content Based Medical Image Retrieval (CBMIR) for effective utilization of medical images based on visual feature analysis for the purpose of diagnosis and educational research. The existing medical image retrieval systems are still not optimal to solve the feature dimensionality reduction problem which increases the computational complexity and decreases the speed of a retrieval process. The proposed CBMIR is used a hybrid approach based on Feature Extraction, Optimization of Feature Vectors, Classification of Features and Similarity Measurements. This type of CBMIR is called Feature Optimized Classification Similarity (FOCS) framework. The selected features are Textures using Gray level Co-occurrence Matrix Features (GLCM) and Tamura Features (TF) in which extracted features are formed as feature vector database. The Fuzzy based Particle Swarm Optimization (FPSO) technique is used to reduce the feature vector dimensionality and classification is performed using Fuzzy based Relevance Vector Machine (FRVM) to form groups of relevant image features that provide a natural way to classify dimensionally reduced feature vectors of images. The Euclidean Distance (ED) is used as similarity measurement to measure the significance between the query image and the target images. This FOCS approach can get the query from the user and has retrieved the needed images from the databases. The retrieval algorithm performances are estimated in terms of precision and recall. This FOCS framework comprises several benefits when compared to existing CBMIR. GLCM and TF are used to extract texture features and form a feature vector database. Fuzzy-PSO is used to reduce the feature vector dimensionality issues while selecting the important features in the feature vector database in which computational complexity is decreased. Fuzzy based RVM is used for feature classification in which it increases the response rate and speed of the retrieval process. This proposed FOCS framework is used to help the physician to obtain more confidence in their decisions for diagnosis and medical research students are zeal to get the essential images successfully for further investigation of their research.

Keywords: Medical Image Retrieval, Texture Features, Optimization, Dimensionality Reduction, Classification, Similarity Measurements

1. INTRODUCTION

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

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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 (Emmanuel *et al.*, 2010; Suganya and Rajaram, 2012) plays a vital role that would locate a desired image from a large varied collection of image database. The radiology department of hospitals is well established with Picture Archiving and Communications Systems (PACS) in which image storage, retrieval and transfer of images are performed using the format of Digital Imaging and Communications in Medicine (DICOM). 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. 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, colorto 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.

1.1. CBMIRGaps

CBMIR has been 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 represented in **Table 1**.

Table 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 (Deserno *et al.*, 2009). The following some of the existing CBMIR systems (Hsu *et al.*, 2009; Xue *et al.*, 2009; Ghosh *et al.*, 2011; Ramamurthy and Chandran, 2012), have been used to retrieve required images from the medical image databases for the purpose of radiologists and medical research students.

1.2. Comparison Algorithm for Navigating Digital Imaging Databases (CANDID)

This system successfully retrieves pulmonary CT images with the same resolution, size and content usingglobal signatures such as texture, shape and color features and regularized distance between probability density functions are used to match signatures from the database of feature vectors.

1.3. Automatic Search and Selection Engine with Retrieval Tools (ASSERT)

This system addresses the issues in the automatic approach of identifying pathology bearing regions and insisted to have human-in-the-loop approach to know anatomical landmarks in the image for High-Resolution Computed Tomography (HRCT) of lung using Texture, Shape, Edges and Gray-scale Properties.

1.4. Medical Image Management System (MIMS)

This Systemaddresses the problem of indexing by the way of representing the image contents initially with context then with the graphical and semantic manner for X ray, CTs of the Head Images using Text and Shape Features with the relationship of JDBC/ODBC bridge.

1.5. Image Map

An Attributed Relational Graphs is used as Image Indexing Method that can map multiple images of organs into a low dimensionality point that allows conception, clustering and operations of data mining based on Spatial Similarity about any number of objects or regions of shape and texture features.

1.6. Image Retrieval in Medical Applications (IRMA)

The medical expert knowledge is incorporated as layers such as raw data, registereddata, feature, scheme, object and knowledgeand medical images are characterized by a ranked structure of ellipses relating image regions with graph matching. This system has

been implemented in a distributed system for various imaging modalities using Global and Local Shape and Texture Features.

1.7. GoldMiner: A Radiology Image Search Engine

This system is an Internet-based search engine developed by the American Roentgen Ray Society (ARRS) to retrieve medical radiography imagesby using keywords in figure captions such as age/modality/sex from the UMLS figure captions from a massive cluster of figures available in peer-reviewed journals and consequences of images displayed in a list or grid manner.

1.8. Cervigram Finder: A Web-Accessible Content-Based Cervicographic Image Retrieval System

This system is developed by the National Library of Medicine which have been operated on a subset of the cervicographic image databases in which the user generates a query image region by recognizing the region of interest on an image using color, texture and size of features through the graphical user interface.

1.9. Spine Pathology and Image Retrieval System (SPIRS)

A Web-based Image Retrieval System for Large Biomedical Database which automate shape extraction and feature indexing methods that are used for efficient retrieval and combining text and image feature for a large biomedical database of digitized spine x-rays exhausting the morphological shape of the vertebral body.

The above developments are revolutionary efforts in CBMIR and have helped potential use in a healthcare environment for radiologist and medical research. These methods have their own merits and drawbacks in their retrieval performance. Successful CBMIR applications can be developed by choosing an efficient algorithm at several stages of indexing and retrieval workflow. The goal of the proposed 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

1.10. Phase I Visual Feature Extraction

Feature extraction (Iakovidis *et al.*, 2009; Akgul *et al.*, 2011; Suganya and Rajaram, 2012) is the base for image retrieval. The extracted visual image features are formed as Feature Vector Database. The features can be classified as general features such as Texture, Shape and Color and domain specific features such as human faces and finger prints. Compared to all the visual features, texture features possess the properties for capturing semantic features in images because it has an inclusive contribution of various grey levels within the image. Also Texture has potentials as periodicity and scale results in a surplus of ways of extracting medical image features. The statistical model based texture feature extraction methods are Gray Level Co-occurrence Matrix, Tamura Features and the spatial frequency and transform based approaches are as Gabor Filter Features and Wavelet Features.

1.11. Phase II: Optimized Feature Selection

Feature selection can be defined as selecting the unification of features among a given larger feature vector database that describes a particular feature set is best. The greater 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. Feature selection is used to reduce the feature space by removing the irrelevant, redundant and noisy features which would declines the computational complexity and upturns the speed of retrieval process. Earlier investigation procedures for dimensionality reduction includes (Wu *et al.*, 2009) Principal Component Analysis, Weighted Multi-Dimensional Scaling Tabu Search Method.

For the past several years Evolutionary Algorithm (EA) operates on the population of possible solutions by relating the presence of the fittest to yield better and better estimates to a solution. The key inspiration for using EA is to search a set of possible solutions simultaneously to find the optimal feature selection with a least runs of algorithm. Most widely used EA for optimizing the features are Particle Swarm Optimization (PSO) (Ye *et al.*, 2009), Genetic Algorithms (GA) (Silva *et al.*, 2011), Gravitational Search Algorithm (GSA) (Rashedi *et al.*, 2009) Ant Colony Optimization (ACO) (Piatrik and Izquierdo, 2009). In general, algorithms can be classified based on the method of evolution. GA population evolves throughout each subsequent population of chromosomes; however, PSO and ACO updates their population based on social behavior.

The individual evolutionary approach is used to identify the potential optimal solutions within a reasonable amount of time. However, this type of CBMIR having an impulsive convergence in which comprehensive optimal fact and the convergence speed is decreased. The difficulty of standard EA are delicate to the choice of parameters that are premature convergence when the particle and group best solutions are confined into local minimums during the search process. A fuzzy adaptive approach is needed to overcome the premature convergence and also to speed up the searching process.

1.12. Phase III: Classification of Features

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. The elements of image feature sets are categorized into a limited number of separable, discrete classes using a mathematical classification process. The steps are: (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 apiece optimized features pixel most looks like the features. The most widely used classification algorithms (Rajendran and Madheswaran, 2010) are K-nearest neighbor, Fuzzy C-Means clustering, Decision Tree, Bayesian Classification.

Some of theinteresting machine learningalgorithms are facilitated to classifymedical images and to enhance the information by using Support Vector Machine, Relevance Vector Machine, (Hong and Chen, 2011; Yogapriya and Vennila, 2012). Mostly all training points are taken uniformly during training but in many real world applications, the inspirations of the training points are different. Precisely, a fuzzy membership is allocated to each input point so that dissimilar input points can make different impacts in learning.

1.13. Phase IV: 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 (Zhu *et al*., 2012) 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 suitableclassified 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.

2. MATERIALS AND METHODS

The above literature survey has motivated to use a hybrid methodology during Feature extraction, Optimization, Classification and Similarity Measurements (FOCS) framework. The proposed system is depicted in **Fig. 1**.

2.1. Methods

- A Texture Feature vector database containing x number of vectors using GLCM and Tamura, x > 100
- Perform Fuzzy Adaptive PSO on the high dimensional feature dataset to select feature set in order to obtain the lower-dimensional feature set
- Train and Test the each of input and output vectors of optimized Feature Sets using Fuzzy RVM Classification
- Apply Similarity Measurements between the Query Image features and Database Image Features using Euclidean Distance

2.2. Phase I: Visual Feature Extraction

Features are used to represent the characteristics of images, extract the most conspicuous features that represent maximum relevant information and form a complete feature vector database. The most widely used features for medical image retrieval is texture features. In this study Gray Level Co-Occurrence Matrix (GLCM) and Tamura texture features are used for feature extraction (Ramamurthy and Chandran, 2012).

2.3. Gray Level Co-Occurrence Matrix Features

The second order statistics are extracted by using Gray Level Co-occurrence Matrix (GLCM). GLCM is used to identify the ways of how certain grey-levels that co-occurs with other grey-levels. The matrix is used to measure the relative frequencies of co-occurrence of grey level combinations within the pairs of pixels in a quantified spatial relationship.
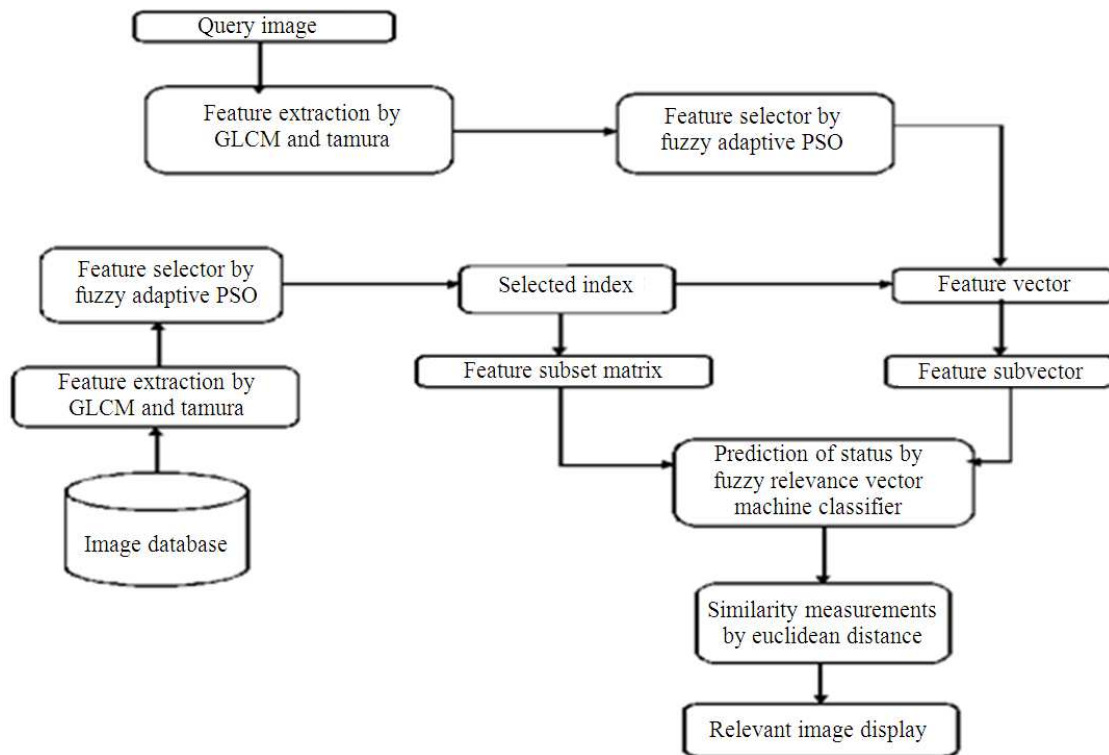
Fig. 1. The proposed fuzzy adaptive hybrid approach based medical image retrieval system using FOCS framework

Given an image G (i, j), let O (i, j) be the position operator and L be the N*N matrix, calculate how often a grey level l (i) that occurs in the location specified by the relationship operator, q, relative to points with grey level l(j). The co-occurrence matrix is defined by dividing the matrix L by aggregating of point pairs that satisfy q. The measure of joint probability is M (i,j) in which pair of points have to satisfy q that have values l (i), l(j). An angle θ and distance d is used to represent a relationship operator. N_m denotes the dimension of co-occurrence matrix and the mean of μ_x and μ_y are defined in Equation 1:

$$\mu_x = \sum_{t=1}^{N_m} im_x(i), \mu_y = \sum_{t=1}^{N_m} im_y(j) \tag{1}$$

and σ_x and σ_y are the standard deviations of m_x and m_y respectively and defined in Equation 2:

$$\sigma_x = \left(\sum_{t=1}^{N_m} m_x(i)(i-\mu_x)^2 \right)^{1/2}, \sigma_y = \left(\sum_{t=1}^{N_m} m_y(j)(j-\mu_y)^2 \right)^{1/2} \tag{2}$$

From M(i,j), μ_x, μ_y, σ_x and σ_y, 14 texture statistical measures of texture features are extracted such as

Angular Second Moment, Contrast, Correlation, Information Measure of Correlation 1, Information Measure of Correlation 2, Maximum Correlation Coefficient, Inverse Difference Moment, Sum Average, Variation, Sum Variance, Difference Variance, Sum Entrophy, Entrophy, Difference Entrophy which would measures the local variations, joint probability occurrence of specified pixel pairs, the sum of squared pixel elements, the closeness of distribution of elements.

2.4. Tamura Features

Tamura extracted six texture features related to human visual perception such as coarseness, contrast, directionality, line-likeness, regularity and roughness.

2.5. Coarseness (T_{crs})

Narrates to distances of distinguished variations of grey levels. At each pixel, find averages in the window of size, differences, values at various directions and finally set the best size. Then identify the coarseness feature by describing the complete distribution of the best sizes over the image instead of averaging over the entire image.

2.6. Contrast (T_{con})

Gives clarity of image in which how grey levels vary in the image and to what level their distribution is inclined to black or white. The second-order and normalized fourth-order central moments of the grey level histogram, the variance and kurtosis are used to define the contrast.

2.7. Degree of Directionality (T_{dir})

Is measured based on the frequency distribution of oriented native edges beside their directional angles using pixel derivatives of an image computed using the sobel edge detector.

2.8. Line Likeyness (T_{lin})

Feature is defined as an average incidental of edge directions that co-occurs in pairs of pixels isolated by a distance in every pixel and would eliminate the weak edges.

2.9. Regularity

Feature is defined as $F_{reg} = 1 \text{-} n(T_{crs} + T_{con} + T_{dir} + T_{lin})$ where n is a normalizing factor and $Sd_{crs} + Sd_{con} + Sd_{dir} + Sd_{lin}$ represents the standard deviation of features such as coarseness, contrast, directionality and linelikeness.

2.10. Roughness

Feature is given by simply adding the coarseness and contrast measures: $FT_{rgh} = FT_{crs} + FT_{con}$.

2.11. Phase II: Optimized Feature Selection

A hybrid approach of Fuzzy adaptive Particle Swarm Optimization is proposed to reduce the dimensionality of feature sets. The selected optimal features are considered for classification. (PSO) is a stochastic algorithm from the imitation of simplified social systems such as bird flocking and fish schooling. A hybrid fuzzy adaptive PSO (Yong-Feng and Shu-Ling, 2009) approach is proposed to overcome the premature convergence also to speed up the searching process. During the evolutionary process, a fuzzy IF/THEN rule system is applied to adaptively regulate the parameters of PSO, such as the inertia weight and learning factors.

2.12. Overview of the Classic PSO

PSO algorithm is based on the particles behavior of a swarm which can be modeled by social behavior of bird flocking or fish schooling. The major advantages of the

PSO algorithm are easy implementation of modest concept, robustness to control parameters, negligible storage requirement and pointing global and local minimum investigations.

The position and velocity of each particles are modernized affording to the following formula and defined in Equation 3:

$$V_{jd}(t+1) = \omega * V_{id}(t) + c_1 * rand(0...1) * (P_{bestj} - X_{jd}(t)$$
$$+ c_2 * rand(0...1) * (G_{besj} - X_{jd}(t)$$

$$X_{jd}(t+1) = X_{jd}(t) + V_{jd}(t+1) \tag{3}$$

where, V_{jd} represents the rate of position change velocity of the jth particle in the dth dimension and t denotes the iteration number, rand $(0...1)$ is a random number between 0 and 1. P_{bestj} is the best position found by the particle j so far. G_{best} is the best position among all particles. c_1 and c_2 are positive random variables evenly distributed in the intervals $[0, c_{1max}]$ and $[0, c_{2max}]$ which could be calculated at each iteration and have the capability to control the relative importance of particles private experience versus swarms social experience for each particle $c_{1max} + c_{2max} \leq 4\omega$ is the inertia weight which is employed to control the global exploration ability and provide a balance between the global and local search capabilities and provide the impact of previous history of velocities on the current velocity. The following weighting function is usually employed and shown in Equation 4:

$$\omega(t) = \omega_{high} - (\omega_{high} - \omega_{low}) \frac{t}{T_{high}} \tag{4}$$

ω_{high} and ω_{low} are the desired higher and lower bounds of the inertia weight. T_{high} is the maximum allowed number of iterations after which the algorithms complete the process. Usually time dependent linearly decreasing value of the inertia weight would be considered to solve global optimization problems.

2.13. Fuzzy Adaptive Particle Swarm Optimization (Fuzzy PSO)

The three parameters C_1, C_2 and ω of PSO are prominently manipulating the performance of an algorithm. The suitable choice of inertia weight ω can provide a balance between global and local optimum

points. The learning factors c1 and c2 determines the influence of personal best $P_{best,j}$ and global best G_{best} particles. Each particle contains n number of features wherein each feature or position is assigned 0 or 1. An assignment of 1 corresponds to the selection of the feature and an assignment of 0 corresponds to its rejection. It is very difficult to design a scientific model to adapt the parameters dynamically because lack of knowledge of searching process. The fuzzy adaptive PSO is proposed to design a fuzzy system which can adapts the inertia weight and learning factors dynamically for image retrieval problems.

2.14. Fuzzy Formulation

The conditional statement is derived by Mamdani-type fuzzy rule which can be used to formulate a fuzzy logic. The output is formulated by the fuzzy control strategy and is represented using a Triangular membership functions from the given input. The AND operator is used to associate the membership values of each rule to generate the membership values in the consequent part of the rule.The deterministic control action is obtained using the method of centroid:

- Low inertia weight and high learning factors can be used when the value of the objective function is low at the end of the run
- High inertia weight and low learning factors should be used when the best fitness is stuck at one value for a long time

2.15. Inertia Weight

The input variable to the fuzzy system is to consider the present best performance evaluation and present inertia weight. The output variable is the change in the inertia weight.

The standardized fitness value SFV is used as an input variable between 0 and 1and is defined in Equation 5:

$$SFV = \frac{FV - FV_{min}}{FV_{max} - FV_{min}} \qquad (5)$$

The first iteration value of FV can be used as FV_{min} for the next iterations. Generally, FV_{max} is a very large value, which is greater than any acceptable feasible solution. Typical inertia weight value is 0 to 0.4. The inertia weight is required to have both positive and negative corrections. Therefore, a range of {-0.1 to 0.1} to be chosen for the inertia weight correction as:

$$\omega^{k+1} = \omega^k + \Delta\omega$$

There are three linguistic values such as S, M and L for Small, Medium and Large that represents the memberships of input and the output variable and can be obtainable in three fuzzy sets of linguistic values: (NA) Not Accepted, ZR (Zero) and (OA) Optimistically Accepted. The Fuzzy rules for variations of the inertia weight are mentioned in **Table 2**.

2.16. Learning Factors

A fuzzy system is developed to adjust the learning factors with Top Fitness (TF) and number of groups for Unchanged top Fitness (UF) as the input variables and the learning factors (c1 and c2) as the output variables. TF reflects the performance of the topmost candidate solution has been found so far. The ranges of TF and UF are normalized into [0, 1]. The Standardized TF Format (STF) is shown in Equation 6:

$$STF = \frac{TF - TF_{min}}{TF_{max} - TF_{min}} \qquad (6)$$

where, TF_{min} is the estimated or real minimum fitness value and TF_{max} is the fitness value greater or equal to maximum fitness value, which could not be an acceptable solution to the optimization problem respectively. UF may be normalized into [0, 1] in a similar way. The values for c1 and c2 are bounded in $1 \leq c1; c2; \leq 2$. The linguistic variables for the inputs and outputs are (OS) Optimistically Small, (OM) Optimistically Medium, (OB) Optimistically Big and (OR) Optimistically Bigger. The fuzzy rules are used to adjust the learning factors (c1 and c2) and shown in **Table 3**.

The triangular membership functions of inputs and outputs are used and Mamdani-type fuzzy rule base is used to formulate the conditional statements which comprise fuzzification process.

2.17. Rule

IF (STF is OB) and (UF is OM),
THEN (ω is OB), (c1 is OM) and (c2 is OM)

The defuzzification strategy is required in which a centroid method is used to obtain a deterministic control action.

Table 2. Fuzzy rules for variations of the inertia weight

$\Delta\omega$		ω		
		S	M	L
SFV	S	ZR	NA	NA
	M	OA	ZR	NA
	L	OA	ZR	NA

Table 3. Fuzzy rules for the learning factors

c_1, c_2		TF			
		OS	OM	OB	OR
STF	OS	OR	OB	OB	OM
	OM	OB	OM	OM	OS
	OB	OB	OM	OS	OS
	OR	OM	OM	OS	OS

2.18. Phase III: Classification of Features

Relevance Vector Machine (RVM) is a popular machine learning techniques based on statistical learning theory and having gorgeous features and thoughtful pragmatic performance. The drawbacks of RVM (Hong and Chen, 2011) are to treat the training points uniformly during training; however, the effect of the training points is different. Fuzzy Relevance Vector Machine is designed to overcome this training difficulty in which a fuzzy membership is assigned to each training input point such that different input points can make different impacts in learning process.

2.19. Overview of the Classic RVM

Relevance Vector Machine (RVM) is a probabilistic model and is proved to be faster than SVMsince it yields an optimum solution with few training samples and it is not necessary for RVM to abstain any regularization parameter during the training phases also there is no necessity for kernel function to fulfill Mercer's condition besides the predictions are probabilistic. For regression problems, the RVM makes predictions based on the function and shown in Equation 7:

$$y(x,\omega) = \sum_{i=1}^{n} w_i K(x, x_n) + \omega_0 \qquad (7)$$

where, K(x,xi) is a kernel function and describing one basis function for each sample in the training set, x_i, i=1, 2…N are adjustable parameters, the training samples and $\{w_i\}$ are the model weights. RVM use hyper planes in order to separate the two parts of the image classes such as relevant and irrelevant.

Input Training Data Set:

$$T = \{(x_i, t_i)\}_{i=1}^{N};$$

Outputthe relevance vectors:

$$T' \subseteq T$$

Predicted unction:

$$y(x, \omega)$$

Terminating Condition: Training Samples $T = \{(x_i, t_i)\}_{t=1}^{N}$.

2.20. Fuzzy RVM

The routine of RVM depends on only a scarce training point that represent ''classical'' samples of classes andmost of the optimized training points can be deliberated of no use. Therefore a notion of RVM with fuzzy membership is called as FRVM and is associated with each training point x_i, so automatically the performance of RVM is fatherly improved and training points would be preserved with various attitudes. Extend the relevance vector approach to the case of classification where it can be desired to predict the posterior probability of class membership given the input x. Generalize the linear model by applying the logistic sigmoid function $\sigma(y) = 1 (1+e^{-y})$ to y (x) and writing the likelihooddefined in Equation 8:

$$P(t \mid w) = \prod_{n=1}^{N} \sigma\{y(x_n;\omega)\}^{t_n} \left[1 - \sigma\{y(x_n;\omega)\}\right]^{1-t_n} \qquad (8)$$

where, the targets $t_n \varepsilon \{0,1\}$.

The most probable weights ω_{MP} have been obtained by finding the minimum over ofthe following Equation defined in Equation 9:

$$-\log\{p(t|\omega)p(\omega|\alpha)\} = -\sum_{n=1}^{N} t_n \log y_n + (1 - t_n)$$
$$\times \log(1 - y_n)] + \frac{1}{2}\omega^T A\omega \qquad (9)$$

With $y_n = \sigma\{y(x_n;\omega)\}$ where the first term of Equation 9 is the summation of error data and the second term of Equation 9 is the regularization span. When introducing the fuzzy membership of the corresponding point, Equation 9 can be changed and defined in Equation 10:

$$-\log\{p(t|\omega)p(\omega|\alpha)\} = -\sum s_n [t_n \log y_n + (1 - t_n)$$
$$\times \log(1 - y_n)] + \frac{1}{2}\omega^T A\omega \qquad (10)$$

The Gradient and Hessian matrix are calculated using statistics and hyper parameters. With respect to different values of s_i, there has been a control over the trade-off of the respective training points (x_i, t_i) in the classification stage. A minor value of s_i makes the corresponding point (x_i, t_i) less important in training. So RVM is the distinct case of FRVM if we set all $s_i = 1$ and if 's' is positive then conclude that optimized feature set could be correctly classified otherwise it is not under the class and defined in Equation 11:

$$S_i = \begin{cases} S_+, y_i = 1 \\ S_-, y_i = -1 \end{cases} \tag{11}$$

2.21. Phase IV: Similarity Measurements

Euclidean distance is used to find the similarity between the query image features and the categorized image features in the database and defined in Equation 12:

$$S_{ED} = \sqrt{\sum_{i=1}^{N} (F_Q[i] - CF_{DB}[i])^2} \tag{12}$$

where, $F_0[i]$ the ith query image is features and $CF_{DB}[i]$ is the corresponding feature in the classified feature vector database and N refers to the total number of images in the database.

3. RESULTS

This proposed FOCS framework is implemented with the image database of 1000 images comprising a different variety of images. These images include some parts of human body like lung, liver, kidney, brain. These images are gray level images and structurally analogous images. **Figure 2** shows some sample images in the database.

3.1. Sample Images

A huge number of features are extracted from the image. This could increase the complexity of the system. So using Fuzzy PSO, we are extracting only the features that are useful in retrieving images from the database. This simplifies the system, increases the accuracy and degrades the complexity of the system. **Table 4 and 5** shows the sample list of feature selected using Fuzzy PSO and optimization results of Fuzzy PSO in respect to Relevance vectors and Particle Fitness Value. The Value of the parameter C1 = 1.35, C2 = 1.35, Inertia Weight = 0.6, the no of particles are 5. The number of images taken for testing is 280 and the numbers of images taken for training is 720. For each image,

selected texture features are given as input to the classification phase. The total number of feature classes are 58. The **Table 6** represents lung, liver, brain and kidney images for testing, training and number of classes. The number of relevance vectors taken for sample training images by using PSO-RVM and Fuzzy PSO-RVM methodology is compared and represented in **Table 7** and depicted in **Fig. 3**.

Table 4. Features selected using fuzzy PSO

Features extracted	Features selected
Angular second moment, Contrast, auto correlation, information measure of correlation, inverse	Entrophy, energy, autocorrelation, contrast, coarseness
Difference moment, variance, Sum entrophy, energy, Coarseness directionality, line likeness, regularity roughness	Directionality, line likeness

Table 5. Sample optimization results of fuzzy PSO

Optimization: fuzzy PSO	Relevance vectors	Particle fitness value
3.8222	9	0.1056
3.8658	9	0.1042
3.5672	9	0.1062
3.4682	9	0.1063
3.8598	9	0.1009
3.5056	9	0.1064
3.8216	9	0.1051
3.4345	9	0.1026
3.8277	9	0.1044
3.4402	9	0.1041

Table 6. Testing, training and No. of classes

	Image features			
Image Type	Lung	Liver	Brain	Kidney
Images for testing	54	66	78	82
Images for training	131	158	186	245
Total no. of images	185	224	264	327
Number of classes	11	13	16	18

Table 7. No. of relevance vectors for No. of training data

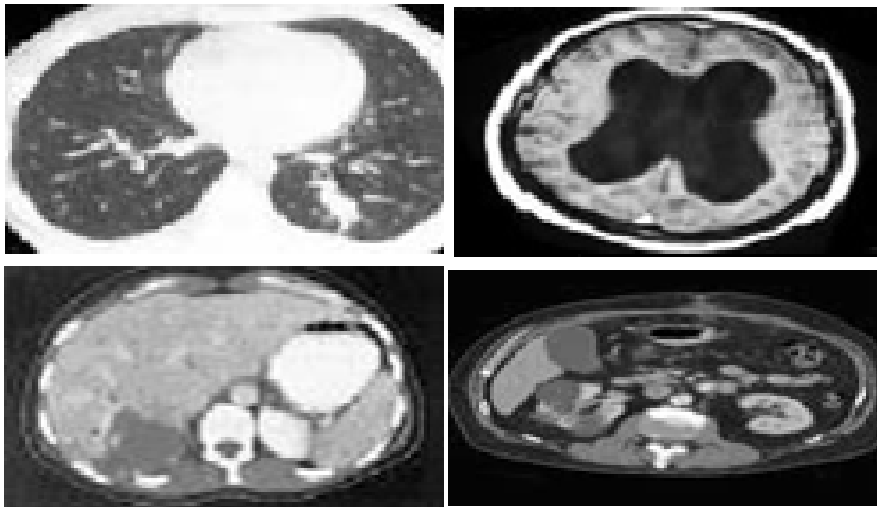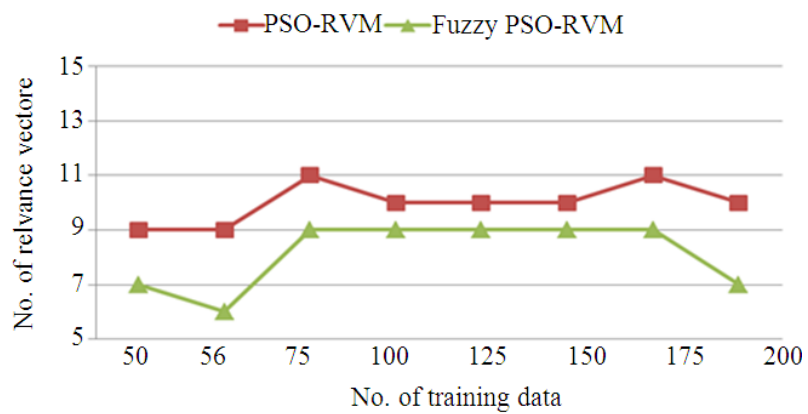| No. of training data	PSO-RVM: No. of relvance	Fuzzy PSO-RVM: No. of relvance vectors
50	9	7
56	9	6
75	11	9
100	10	9
125	10	9
150	10	9
175	11	9
200	10	7

Fig. 2. Sample images

Fig. 3. PSO-RVM and fuzzy PSO-RVM relevance vectors and training samples
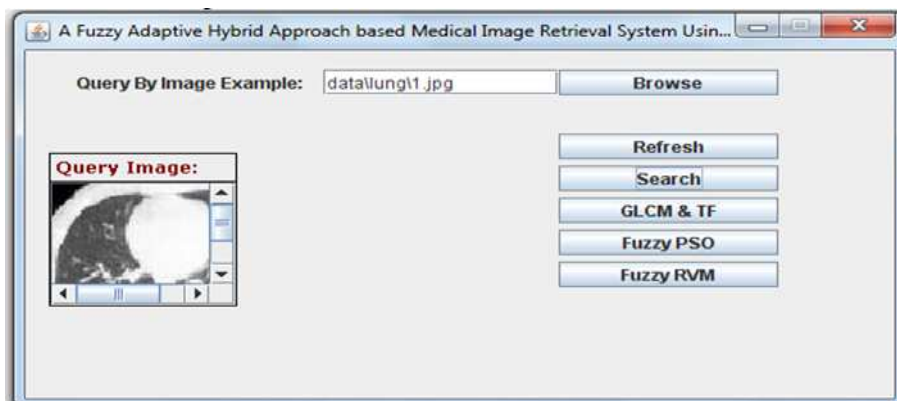

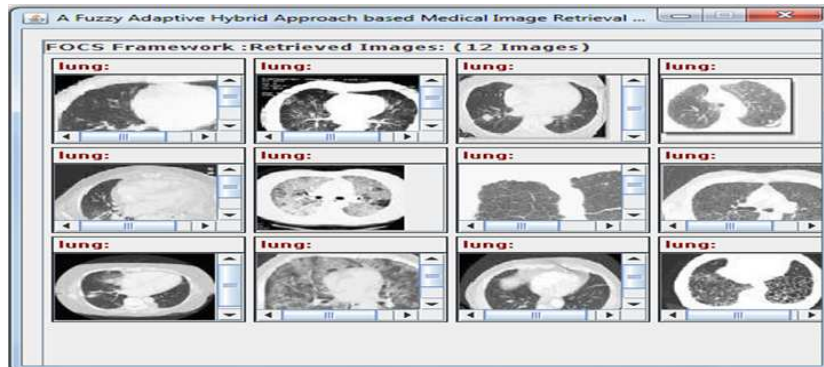**Fig. 4.** Sample query image "lung.jpg"
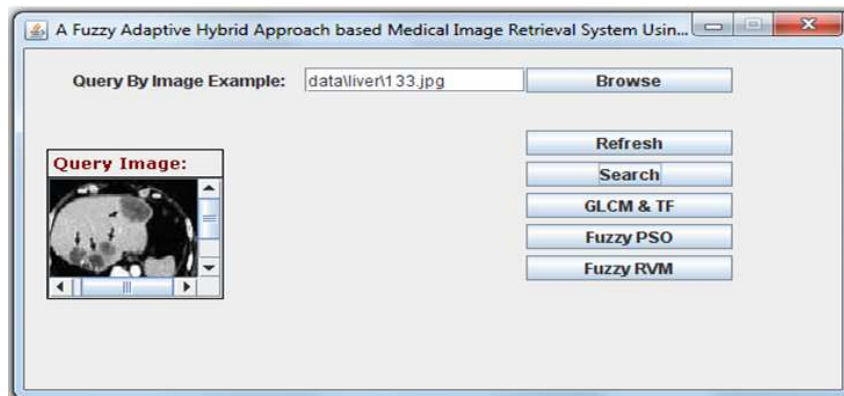
Fig. 5. Output of retrieved images of "lung.jpg"
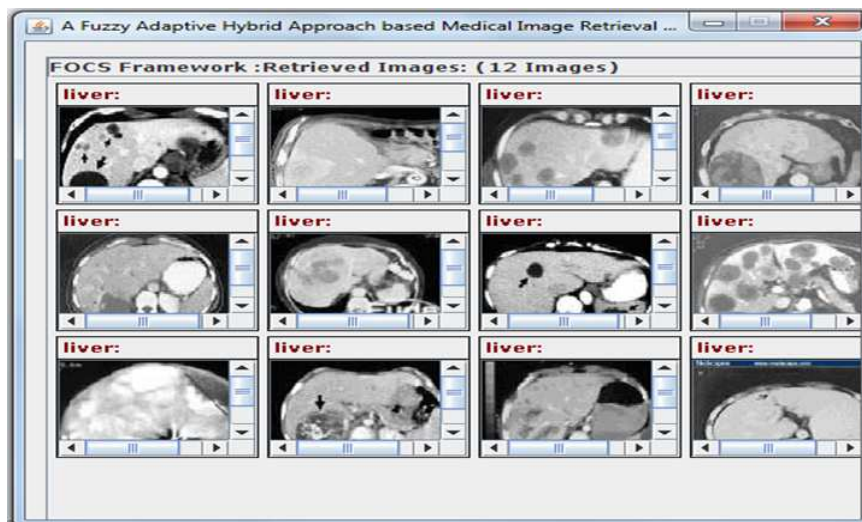

Fig. 6. Sample query image "liver.jpg"

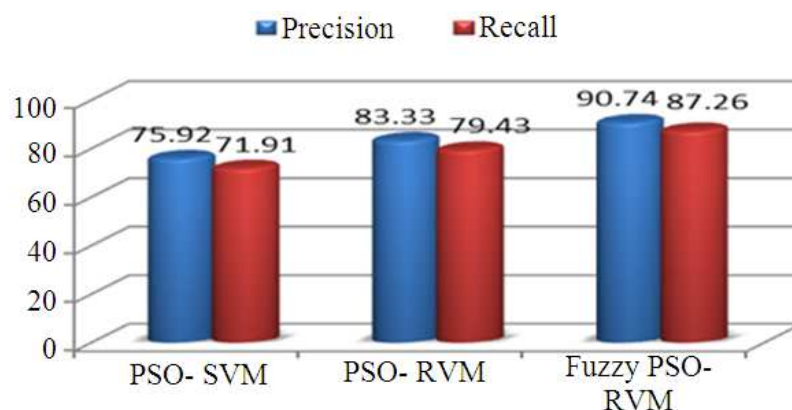**Fig. 7.** Output of retrieved images of "liver.jpg"

Fig. 8. Precision-recall performance analysis

Table 8. Comparision of proposed method

Methods	Overall features	Corrected features	Model Error	Precision	Recall
PSO-SVM	54	41	0.099	75.92	71.91
PSO-RVM	54	45	0.028	83.33	79.43
Fuzzy PSO-RVM	54	49	0.017	90.74	87.26

3.2. Comparisons on Retrieval Performance

The retrieval performance is evaluated using precision and recall. Precision gives retrieval accuracy while recall gives ability of retrieving relevant images from the database. The Precision (P) and Recall (R) are then defined as:

$$p = \frac{r}{n_1} = \frac{\text{Number of relavant images}}{\text{Number of retrieved images}}$$

$$R = \frac{r}{n_2} = \frac{\text{Number of relavant images}}{\text{Total number of retrieved images in the Database}}$$

The **Fig. 4 and 5** represent the sample query image and output of retrieved images of lung. The **Fig. 6 and 7** represent the sample query image and output of retrieved images of liver and **Fig. 8** represent Precision-Recall performance analysis.

4. DISCUSSION

Thisstudy includes analysis of proposed system in terms of Feature Extraction, Optimization, Classification and Similarity measurements (FOCS Framework) applied to retrieve efficient images based on user request. Initially, database with 1000 real time medical images were used for testing theproposed CBMIR

system. In feature extraction phase, the results were moderately good and it has given about 90% of the performance for texture feature extraction. In optimized feature selection and classification phase, most of the images perform well and it gives about 90% of the performance of this phase. In retrieval phase, approximately all the images carry out well and conventional Euclidean distance method was used for retrieval and it has given better performance result.

For measuring retrieval performance, traditional parameters such as precision and recall measurements were used.The effectiveness of the optimization, classification testing, potential performance and accuracy is analyzed using PSO-SVM, PSO-RVM and Fuzzy PSO-RVM with 131 training samples and 54 testing samples of lung images. For the 54 testing samples, the precision and recall of PSO-SVM, PSO-RVM Fuzzy PSO-RVM is represented in **Table 8** and corresponding graphical representation is shown in **Fig. 8**, indicate that the proposed method has more accuracy than the remaining two methods.

The Precision and Recall performance analysis shows that PSO-SVM and PSO-RVM control require more time and iteration to converge. The proposed Fuzzy PSO-RVM has grasped faster in terms of iteration to converge and the relevance vectors chosen based on Fuzzy Rules has reduced the computational complexity based on considering its detection accuracy.

This makes the proposed FOCS framework more feasible for CBMIR Systemand helpful for physician and medical research students.

5. CONCLUSION

A hybrid approach based FOCS framework is proposed for effective retrieval of medical images, it comprises several benefits when compared to existing CBMIR. Texture Features are extracted using GLCM and TF and stored in a feature vector database. Fuzzy-PSO is used to reduce the feature vector dimensionality issues while selecting the important features in the feature vector database in which computational complexity is decreased. Fuzzy based RVM is used for feature classification in which it increases the response rate and speed of the retrieval process. Euclidean distance is used to identify the similarity between classified features and query image features. Results reflect that the proposed system using multiple features with optimization, classification and similarity measurements outperforms with respect to retrieval accuracy and precision as compared with existing CBMIR. This proposed FOCS framework is used to help the physician to obtain more confidence in their decisions for diagnosis and medical research students are zeal to get the essential images successfully for further investigation of their research.

6. ACKNOWLEDGEMENT

7. REFERENCES

Akgul, C.B., D.L. Rubin, S. Napel, C.F. Beaulieu and H. Greenspan *et al*., 2011. Content-based image retrieval in radiology: Current status and future directions. J. Digital Imag., 24: 208-222. DOI: 10.1007/s10278-010-9290-9

Deserno, T.M., S. Antani and R. Long, 2009. Ontology of gaps in content-based image retrieval. J. Digital Imag., 22: 202-215. DOI:10.1007/s10278-007-9092-x

Emmanuel, M., D.R.R. Babu, J. Jagdale, P. Game and G.P. Potdar, 2010. Parallel approach for content based medical image retrieval system. J. Comput. Sci., 6: 1258-1262. DOI: 10.3844/jcssp.2010.1258.1262

Ghosh, P., S. Antani, L.R. Long and G.R. Thoma, 2011. Review of medical image retrieval systems and future directions. Proceedings of the 24th International Symposium on Computer-Based Medical Systems, Jun. 27-30, IEEE Xplore Press, Bristol, pp: 1-6. DOI: 10.1109/CBMS.2011.5999142

Hong, L.I. and G. Chen, 2011. Image classification technique based on fuzzy-relevance vector machine. J. Inform. Computat. Sci., 8: 3989-3995.

Hsu, W., S. Antani, L.R. Long, L. Neve and G.R. Thoma, 2009. SPIRS: A web-based image retrieval system for large biomedical databases. Int. J. Med. Inform., 78: S13-S24. DOI: 10.1016/j.ijmedinf.2008.09.006

Iakovidis, D.K., N. Pelekis, E.E. Kotsifakos, I. Kopanakis and H. Karanikas *et al*., 2009. A pattern similarity scheme for medical image retrieval. IEEE Trans. Inform. Technol. Biomed., 13: 442-450. DOI: 10.1109/TITB.2008.923144

Piatrik, T. and E. Izquierdo, 2009. Subspace clustering of images using ant colony optimisation. Proceedings of the 16th IEEE International Conference on Image Processing, Nov. 7-10, IEEE Xplore Press, Cairo, pp: 229-232. DOI: 10.1109/ICIP.2009.5414503

Rajendran, P. and M. Madheswaran, 2010. Hybrid medical image classification using association rule mining with decision tree algorithm. J. Comput.

Ramamurthy, B. and K.R. Chandran, 2012. Content based medical image retrieval with texture content using gray level co-occurrence matrix and k-means clustering algorithms. J. Comput. Sci., 8: 1070-1076. DOI: 10.3844/jcssp.2012.1070.1076

Rashedi, E., H. Nezamabadi-Pour and S. Saryazdi, 2009. GSA: A gravitational search algorithm. Inform. Sci., 179: 2232-2248. DOI: 10.1016/j.ins.2009.03.004

Silva, S.F.D., M.X. Ribeiro, J.D.E.S.B. Neto, C. Traina-Jr and A.J.M. Traina, 2011. Improving the ranking quality of medical image retrieval using a genetic feature selection method. Decision Support Syst., 51: 810-820. DOI:10.1016/j.dss.2011.01.015

Suganya, R. and S. Rajaram, 2012. Content based image retrieval of ultrasound liver diseases based on hybrid approach. Am. J. Applied Sci., 9: 938-945. DOI: 10.3844/ajassp.2012.938.945

Wu, J., X. Wang, D. Yan, C. Wei and Y. Zhang, 2009. Method for medical image retrieval based on frequency layer feature. Proceedings of the International Conference on Information Technology and Computer Science, Jul. 25-26, IEEE Xplore Press, Kiev, pp: 622-624. DOI: 10.1109/ITCS.2009.321

Xue, Z., S. Antani, L.R. Long, G.R. Thoma, 2009. A system for searching uterine cervix images by visual attributes. Proceedings of the 22nd IEEE International Symposium on Computer Based Medical Systems, Aug. 2-5, IEEE Xplore Press, Albuquerque, NM., pp: 1-5. DOI: 10.1109/CBMS.2009.5255319

Ye, Z., B. Xia, D. Wang and X. Zhou, 2009. Weight optimization of image retrieval based on particle swarm optimization algorithm. Proceedings of International Symposium on Computer Network and Multimedia Technology, Jan.18-20, IEEE Xplore Press, Wuhan, pp: 1-3. DOI: 10.1109/CNMT.2009.5374753

Yogapriya, J. and I. Vennila, 2012. Medical image retrieval system using ggre framework. Proceedings of the International Conference on Pattern Recognition, Informatics and Medical Engineering, Mar. 21-23, IEEE Xplore Press, Salem, Tamilnadu, pp: 246-251. DOI: 10.1109/ICPRIME.2012.6208352

Yong-Feng, X. and Z. Shu-Ling, 2009. Fuzzy particle swarm clustering of infrared images. Proceedings of 2nd International Conference on Information and Computing Science, May 21-22, IEEE Xplore Press, Manchester, pp: 122-124. DOI: 10.1109/ICIC.2009.139

Zhu, Z., C. Zhao and Y. Hou, 2012. Research on similarity measurement for texture image retrieval. PLoS ONE, 7: e45302-e45302. DOI: 10.1371/journal.pone.0045302