Asian Journal of Information Technology 17 (2): 98-113, 2018
ISSN: 1682-3915

Content-Based Image Retrieval Based on High Level Labels

Nasibeh Esmaeili Shahmirzadi and Ibrahim Chaoudi
Department of Computer Science, Lobachevsky State University of Russia, Nizhny Novgorod, Russia

Abstract: Text-based and content-based retrieval are considered as two main approaches of the image-based retrieval. Challenges faced by both approaches direct researchers toward combined approaches and semi-automatic retrieval by the collaboration of the user in the cycle of retrieval specifically in the field of medical issues. Therefore, in this study, a system of image retrieval is introduced which provides user with two types of query based on keywords and images. After retrieval of the initial results, proposed system performs retrieval operation in a semantic manner and semi-automatically using feedbacks received from the user and high level semantic tags allocated to the images. By means of a hierarchical ST and a type of learning by user feedbacks, system is able to respond to diverse queries in the field of image retrieval. According to tests, proposed system is of acceptable precision.

Key words: ST, image retrieval, learning, lung, queries, allocated

INTRODUCTION

Image retrieval is an important field of research which attracted a lot of attention in recent years (Gevers and Smeulders, 2004). Two basic approaches for image retrieval is suggested by researchers: text-based and content-based retrieval (Smeulders *et al*., 2000). In the former, the process of retrieval is conducted by using keyword and assigning them to the images and according to it, format of the query of the user is by words. As such, criterion of recognition of similarity between images is through fitting keywords assigned to them (Muller *et al*., 2001). These approaches face two main challenges (Smeulders *et al*., 2000; Wenyin *et al*., 2001):

- Time-consuming and expensiveness of the process of assigning keywords to images
- Optional selection of keywords representing the images by user

Content-based retrieval was introduced in response to shortcomings of the above approach (Gevers *et al*., 2004; Muller *et al*., 2001). In this type, retrieval process is based on low-level visual features such as color, texture and shape. The most significant advantage of this method compared to the first method is the possibility of extracting vectors of visual features in an automatic way (Muller *et al*., 2001; Figueiredo *et al*., 2001). This issue improves the speed of the annotation of the images considerably. However, content-based retrieval faces serious challenges that is the presence of semantic gap between low and high-level visual features of the images (Smeulders *et al*., 2000; Figueiredo *et al*., 2001). Such challenges directed researchers toward using combined and semi-automatic approaches of retrieval by collaboration of the user in the cycle of retrieval (Wenyin *et al*., 2001; Hyvonen *et al*., 2004; Shevade *et al*., 2003). In this way, semi-automatic retrieval by user collaboration in the cycle of retrieval and combined usage of keywords and low-level visual features for description of images is the main issue of this study. Collaboration of user in the cycle of retrieval in the form of relevance feedbacks leads to improvement of precision and efficiency of the process of retrieval (Brahmi and Ziou, 2004; Xu *et al*., 2003; Panagi and Dasiopoulou, 2006).

In this study, a system of image retrieval is presented which conducts lung image retrieval in a semi-automatic manner using user's relevance feedbacks and high-level semantic tags as signed to images.

Literature review: Available systems of image retrieval are either based on text-based approach (Muller *et al*., 2001) or content-based ones (Gevers *et al*., 2004; Figueiredo *et al*., 2001). A group of systems use the combination of images as well (Xu *et al*., 2003; Panagi and Dasiopoulou, 2006). Using keywords for retrieval is considered by researchers owing to being user-friendly and inherent nature of the words and query through them

Corresponding Author: Nasibeh Esmaeili Shahmirzadi, Department of Computer Science,
Lobachevsky State University of Russia, Nizhny Novgorod, Russia

will yield suitable results. Of course, this method can be combined with methods of visual content search, so that, user can have further control over the search. In this way, relevance feedback is one of the complementary techniques in the field of semantic retrieval of the images which brings the retrieval process close to user request by using user opinions in a semantic manner (Zhu *et al*., 2000; Ion *et al*., 2007; Agarwal *et al*., 2013). Basis of the performance of the presented retrieval system of this research is using the method of relevance feedback and performing a type of learning operation in each stage of interactive retrieval. By Hentschel *et al*. (2006) in a manner similar to the proposed method, problem of retrieval is addressed in literature based on feedback images. In this system, a type of one-to-one relationship between semantic classes and image groups having common semantic tags is disseminated. In fact, this system groups images based on relevant and irrelevant feedbacks of user and therefore in the context of learning it is in line with the proposed system but it differs from it in using learning method due to certain issues of grouping. Moreover, in the context of supervised learning, Carneiro *et al*. (2007) provides a new method using a semantic dictionary for application of retrieval systems which includes a learning method for estimation of the probable distribution of content in relation to the images of the database. Learning process of the aforesaid method operates based on the semantic classes assigned to images. Furthermore, similar to the proposed system, (Borji and Litti, 2012;Wenyin *et al*., 2001; Lu *et al*., 2000; Yang *et al*., 2001; Carneiro and Vasconcelos, 2005) used methods of relevance feedback in both text-based and content-based contexts and in this way, they don't provide the absolutely semantic performance intended by the proposed system, so that, in Wenyin *et al*. (2001), weighted sum of the similarity based on keywords and visual features are used for evaluation of the percent of similarity between the image and the query. Performance of the system for semantic query is based on the exact adaptation of the words and as such, it loses the possibility of retrieval of images corresponding to query solely due to assigning other tags to those images. Lu *et al*. (2000), Puviarasan *et al*. (2014), Wang and Zang (2012), Borji and Litti (2013), Liu and Yang (2013) use a similarity metric for measurement of the overall relation between an image with the actual aim of the user by keywords and low-level content. In this metric, relationship similarity is explored for exact adaptation of the query keywords and semantic and visual similarity of the database image with relevant and irrelevant sets obtained from user interaction. In line with this issue in the context of combined usage of meaning and visual features of the image, a research is conducted by Petrakis *et al*. (2006) which provides a standard framework in accordance with this usage. Performance of the system is based on assigning combinations of meaning and visual content of the organized and hierarchical parts of the image. A system is introduced by Shah-Hosseni (2007) which utilizes the technique of relevant feedback for directing content searches based on visual features in about visual queries in next stages of the interaction toward semantic searches. In this system, images of the database belong to semantic classes with varying levels of the relevance and initial search is done based on content characteristics of the images. It must be pointed out that method of highlighting relevance feedbacks in this system is relative and gets a value between 0 and 1.

Similarly, a method is introduced by Xiang and Zhou which uses the method of relevance feedback and query based on keyword and low-level visual content. This algorithm is called Word Association via. Relevance Feedback or (WARF). In this research, thesaurus (a type of keywords) is created automatically based on statistical analysis of the frequency of the keyword as well as that of relevant words. Of course, in this system, capability of construction of the network based on WARF is made possible after presenting user feedbacks with more than one relevant image. Similar to the proposed system, the most important source of semantic information and comprehending the user is through interaction with him. In Table 1 as can be seen the summary of methods of retrieval of high-level images in medicine.

In a manner similar to the application of ST in the proposed system, Carneiro and Vasconcelos (2005b) presents a dynamic semantic hierarchy as well as a metric of semantic similarity for improvement of the precision of the semantic adaptation in a retrieval operation. ST used in this study includes semantic relations of the image with a set of relevant keywords so that similarities of the system are addressed in two forms word-word similarity and tags and queries of the user. First, retrieval is performed by exact adaptation of query keywords and that of ST and then, after interaction with user, keywords assigned to relevant and irrelevant images serve as another query for finding better results. In general, considerable diversity of images and meanings contained in them ignorance of synonym tags and polysemy are important shortcomings of methods presented in this field (Xu *et al*., 2003; Carneiro and Vasconcelos, 2005a, b) (Puviarasan *et al*., 2014; Puviarasan *et al*., 2014; Wang and Zhang, 2012; Hill *et al*., 2012).

Table 1: Summary of methods of retrieval of high-level images in medicine

Category/representations/cues	References
Photometric	
Grayscale and color	Histograms (Comaniciu *et al*., 1999; Lim and Chevallet, 2005; Shyu *et al*., 1999; Cauvin *et al*., 2003)
	Moments (Zhu *et al*., 2003; Mao and Jain, 1992)
	Block-based (Guld *et al*., 2005; Lubbers *et al*., 2004; Doyle *et al*., 2007)
Texture	Texture co-occurrence (Cauvin *et al*., 2003; Gletsos *et al*., 2003; Zhu *et al*., 2003; Rahman *et al*., 2007; Mao and Jain, 1992)
	Fourier power spectrum (Zhu *et al*., 2003)
	Gabor features (Shyu *et al*., 1999; Gletsos *et al*., 2003)
	Wavelet-based (Lim and Chevallet, 2005)
	Haralick's statistical features (Balmachnova *et al*., 2007)
	Tamura features (Lubbers *et al*., 2004)
	Multiresolution autoregressive model (Comaniciu *et al*., 1999)
Geometric	
Point sets	Shape spaces (Antani *et al*., 2004)
Contours/curves	Polygon approximation (Balmachnova *et al*., 2007)
	Edge histograms (Cauvin *et al*., 2003; Mao and Jain, 1992; Qian and Tagare, 2005)
	Fourier-based (Shyu *et al*., 1999; Cauvin *et al*., 2003; Balmachnova *et al*., 2007)
	Curvature scale space (Golland *et al*., 2005)
Surfaces	Level sets/distance transforms (Gletsos *et al*., 2003; Bansal *et al*., 2007)
	Gaussian random fields (Toews and Arbel, 2007)
Regions and parts	Statistical anatomical parts model (Pokrajac *et al*., 2005)
	Wavelet-based region descriptors (Huang *et al*., 2005)
	Spatial distributions of ROIs (Sasso *et al*., 2005)
Other	Global shape (size, eccentricity, concavity, etc.) (Cauvin *et al*., 2003; Guld *et al*., 2005 Qian and Tagare, 2005; Liu and Yang, 2013)
	Morphological (Gletsos *et al*., 2003;Agarwal *et al*., 2007; Kwak *et al*., 2002)
	Location and spatial relationships (Guld *et al*., 2005; Gletsos *et al*., 2003; Liu and Yang, 2013; Agarwal *et al*., 2007; Chaturvedi *et al*., 2014)

MATERIALS AND METHODS

Proposed model: Since, it is possible to present two types of query based on keywords and sample image in this system, its performance differs according to the used query. In fact, by presenting two forms of queries, proposed system intents to complete the process of semantic retrieval in such a way that even in the mode of image query it can replace the process of semantic query with content one based on low-level visual features of the images. For a type of learning from user, proposed system applies a method of relevance feedback and a hierarchical ST including the set of synonyms as semantic nodes of the network to improve its efficiency in retrieval of relevant images. In this way, process of image retrieval yields results in highest level of relevance to the meaning intended by users in accordance with the specific structure of ST as well as considering relevance feedbacks of users presented either directly or indirectly for retrieved images. Robustness of the proposed system for semantic retrieval and supporting the capability of retrieval of synonyms illustrates a semantic concept and clarification of the meaning of words based on their membership in a certain semantic group due to the used ST and its operational robustness for semantic retrievals through calculation of ST among semantic nodes of ST and using these similarities for a new query based on meanings assigned to a feedback image. In addition, it is possible to retrieve images relevant to the query of the user based on exact and inexact adaptation in the form of ST with keywords assigned to them if there is no direct result rather than random retrieval. Moreover, due to presence of a unique identity for each set of semantic synonyms in the hierarchical structure of the proposed system, it is possible to use polysemy. Relationships of this study can be considered as the generalized form of Rocchio (Lu *et al*., 2000; Carneiro and Vasconcelos, 2005a, b). Weighted sums applied for above relations are all relative and in fact, they express the relative weight of each node in expression of the meaning of the image. In similarity section, weight values imply to the relative validity of the query keywords in corresponding node. In this way, conceptual unit based on relevance feedbacks presented in each stage conduct conceptual retrievals which are closer to the meanings intended by user.

Model components: Main components of the proposed system are ST, search engine and conceptual unit. Figure 1 illustrates the main components of the proposed system and the way they are connected to each other. Sample images and Keyword query are determined by user. Hierarchical ST as well as a communication network for connecting meanings available in ST to images of database. Search engine retrieves the images

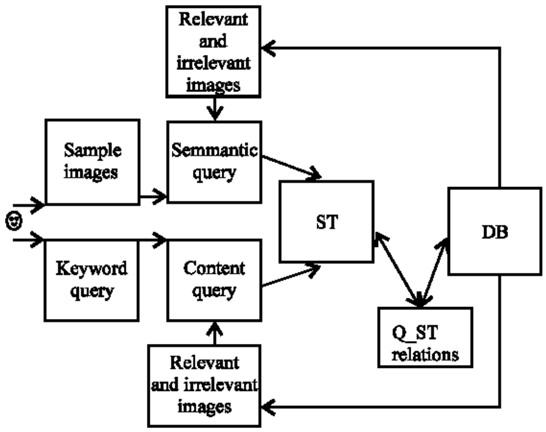

Fig. 1: Main components of proposed model

based on the type of query like semantic and content and information network. The Q-ST is semantic similarity that determined by red rectangle

According to Fig. 1, user communicates with the query unit of user interface through query. In this system, system information network including visual database, hierarchical ST as well as a communication network for connecting meanings available in ST to images of database, so that, search engine retrieves the images based on the type of query and information network. Unit of content search is launched by search engine and after this stage, retrieved images are shown to the user and through the unit of relevance feedback, user provides feedbacks for retrieved images based on similarity to the intended meaning. Based on the type of initial query, content unit decomposes the factors contributing to new query and presents to the unit of query modification. For query based on sample image, set of positive and negative feedback samples and for query based on keywords, set of positive and negative samples are used in addition to the initial query for making the new query. Unit of query modification computes the ST of database images with new modified query according to above factors and information network of and accordingly, it retrieves new images which are closer to the meanings intended by user. Unit of query modification is allocated to a type of learning from user's feedback for improvement of the results of current retrieval in the form of valuation of the images of the database according to the value of ST to factors contributing to the new queries obtained from the previous stage of interactive retrieval. In what follows, main components of the proposed system and their performance are explained in detail.

Semantic Tree (ST): ST is one of the most important components of the proposed system. ST used in this method can be regarded as a tree whose node are organized as a set of synonym keywords and connection of nodes based on a correct hierarchy of generalization-specialization relations, so that, general concepts are in higher level of hierarchy and more specific ones are in lower levels. In this ST, each node includes several synonyms and a membership level or a weight is assigned to each of the keywords of the node for belonging to the group.

It must be noted that proposed method tries to present an efficient solution for retrieval of image with high level of meanings and since, concepts corresponding to the dimensions of the lung fall within the category of high level concepts, STs containing such concepts are used in the proposed system. Figure 2 represents a part of ST used in this research.

In proposed system, each image is not assigned to each of the keywords available in ST. But each image is related to each of the nodes of the network with a specific weight and as stated earlier, it includes a set of synonyms. Therefore, in the proposed system, two weight sets are defined and used in this stage:

- Weight values yield the membership level and validity of the synonym keywords in each ST node
- Weight values illustrate the relationship between each node and images of the database which imply to the ability of the set of synonyms to express the content of the meaning of images

Using the hierarchical structure, in addition to the benefit of retrieval of synonyms and clarification of the meaning of words which can be inferred by the set embedded in it, similarity of keywords can be found from the general relationship as well as their belonging to various hierarchies, so that, two keywords belonging to different hierarchies have no common ST. In other words, there is a parent-child relationship between levels of ST and it is clear that each semantic set in lower levels which are themselves child of another semantic set of higher levels, inherit characteristics of their parent. Regarding ST of two keywords in a hierarchy, it can be said that the nearest common ancestor determines the similarity between them and due to the heritage relationship, they have common specifications of the common ancestor. It must be noted that used ST addressed the issue of polysemy to some extent and a word with different meanings can be in different semantic sets.

For updating, ST is initially adjusted manually with synonyms of semantic nodes of the network as well as their membership validity in corresponding nodes.

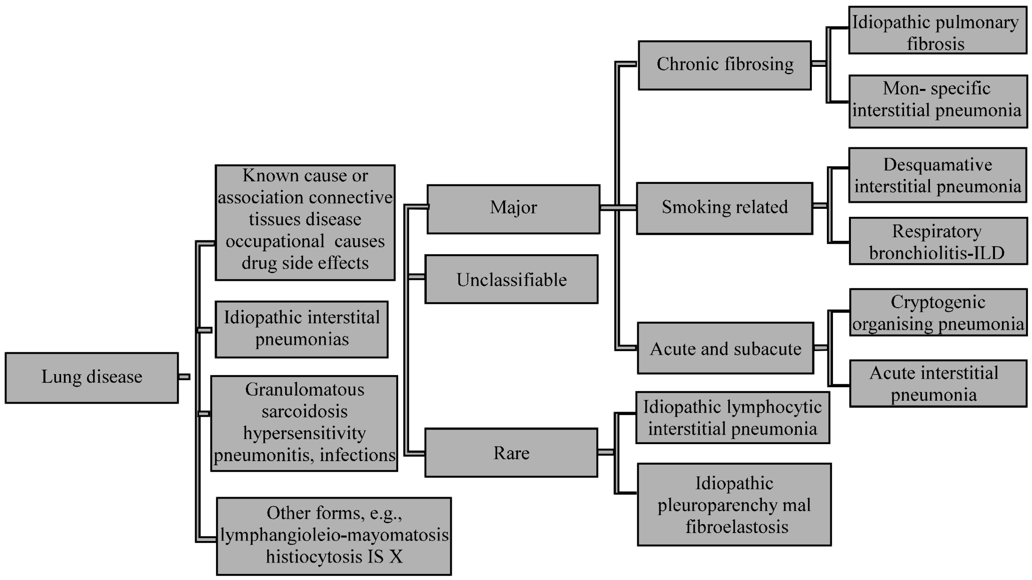

Fig. 2: A hierarchical ST for lung diseases based on keywords

Extension of ST is done semi-automatically with the aid of user, so that, at the entrance of a new research and or if the keywords used in query is not available in ST structure, user is asked to provide to keywords one of which will be a generalization of the new word and another one is a synonym for it. If a synonym is present in ST for that word, new word is added as a new synonym in the level of corresponding node and if it is present, only a generalization of it will be added to the node as a new characteristic of the semantic node or its child in ST and all relationships of the generalization node are extended to the characteristic node. If synonym concepts or a generalization of the new word is not available in network structure, new keyword can create a new branch in hierarchical structure, so that, by entering other meanings to this semantic field, this hierarchy is completed and ST will be more comprehensive.

Simantic Similarity (Q_St): In proposed system, user is allowed to provide two types of text queries. In this case, for retrieval of images, keywords are first searched in ST and after finding nodes containing them, images relevant to the nodes are valued according to their nodes.

To find the weight of each image of database in similarity with query, two weight values; image (j), node (k), value (i) and node (k) are used. In other words, both the membership level of keyword i and relevance weight of the image j to semantic node k contribute to the similarity of image i and keyword k. After calculation of the value of all images of the database according to the obtained values in a descending manner, so that, based on and arbitrary number expressed by user, the most valuable images of the set can be retrieved. Since, OR operation is used, there is no limitation for gaining high value among images to be retrieved.

Regarding and operation, the method is different so that by considering AND relationship between query keywords, user explicitly states that he asks for images with a meaning comprising of all keywords. In this case, keywords are searched in ST individually and after finding nodes containing them, relevant images are valued according to the weight. However, since, user requires the combination of words and asks for images which include all intended keywords, final value of images is computed according to ranks.

After computation of the final value, each of the images which gain higher value according to the relevance represents higher level of the meaning intended by user. In this way, images re ranked according to their value to be presented to the user. On this basis, images which gain higher value in ranking attain in general higher percent of the meaning intended by user.

Content similarity: In this study, two methods graphing and image processing are used for searching content and finally, their results are compared and the precision of the algorithm will be computed. In next studies, various stages of each method are described.

Graphing: The first step is to draw the graph corresponding to the image in two steps. First step is to determine the boundary points of the graph. For this end, points of image edges are used. Second step is to find lines between points for which algorithms based on Minimum Cost of Path (MCP) are used. It must be pointed out that each image of lung is divided into two parts right and left and all stages are applied to each part of the image and the result is the sum of the results of both parts.

Finally, we have a set as follows in which N is the number of points (graph vertices) and a cost function is defined between each two points which is computed using MCP Algorithm.

Boundary points: In image of both normal and abnormal lungs, key points are determined and for this, points located in edges of the image are used so that initially, all boundary points are determined and then, points which are critical are extracted from them. Of course, this stage is completed manually by an expert and it can be automated using a method such as artificial neural networks and genetic algorithm.

Lines between points: At this stage, points determined in previous step will be connected to each other. For this purpose, various algorithms based on MCP are used and algorithm used in this research is explained in algorithm 1. Finally, points are considered as the vertices of the graph and the distance between two points is taken as the weight of the line between them. Final arrangement after applying algorithm is depicted in Fig. 3 and 4.

Algorithm 1: MCP

```
MCP (c)
L.insert (All points)
While (L)
M←L
M.distance (all_remaining_points)
L.nearest_point
Exit (0)
```

Determination of the area of tumor: In this step, graph obtained previously is processed. This step has two parts. First, boundaries of the tumor are highlighted by dashed line and second, area of the highlighted region is computed. These two stages are explained.

This step is also accomplished in two parts. In first step, center of the image is determined and its distance from all vertices of the graph are computed and distances are arranged in array in a manner that highest point is taken as starting point and its distance from the center is written in the first cell and then, we move clockwise and find the values of other arrays. In Fig. 4, distance between graph vertices and image center are determined by red lines.

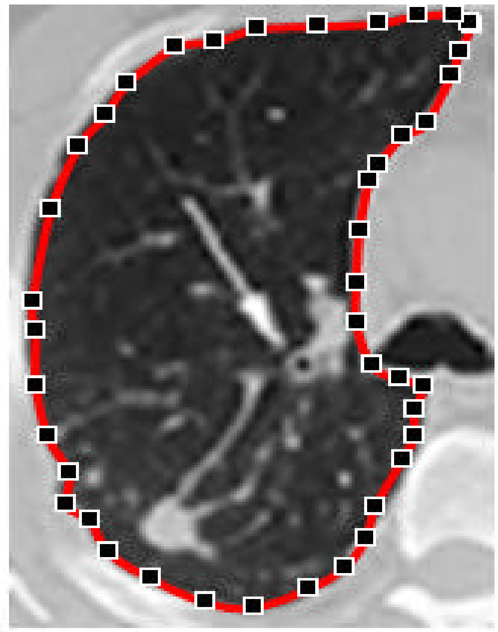

Fig. 3: Boundary points small rectangles are points and considered as the vertices of the graph points are connected by red lines

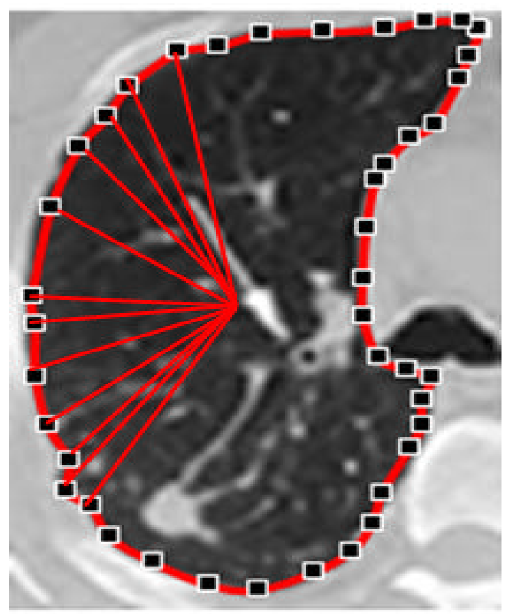

Fig. 4: Red lines are representation of the distance between graph vertices and image center. The graph vertices are shown by small rectangles

At the end of this step, two arrays are created as a and b whose elements are the distances between the center of each image and graph vertices. In the next step, two arrays created in the first step are compared to each other and if the difference between two analogous elements exceeds a threshold value, it will be regarded as the sign of the presence of an abnormal tumor in lung. This threshold is obtained using a trial and error method and in tests, this value is set equal to 5.

Therefore, at the end of this step, difference between distances are computed and compared to the threshold value and if it is more than the threshold, analogue vertices are marked as shown in Fig. 5 and consequently, tumor region is determined.

Area of tumor: For this step, triangulation method is used. As can be seen in Fig. 5, each image is divided into many triangles whose area can be calculated and by summing them up, overall area can be found. For this end, overall area relation is used. Calculation is performed for both images and then, area of both image is obtained and their difference will give the area of the tumor.

Previous stages are done using graphing method and area of the tumor is obtained. To determine that how precise is the work, above stages are completed using a method common in image processing. At the end, results are compared and the precision is evaluated. The method used here includes two steps. First, boundary of tumors is determined, so that, the region of tumor can be clearly separated from the other parts of the image. Then, area of the extracted region is computed.

Separation of the tumor: For this purpose, separation by colors is used. In this way, difference in color of the normal and abnormal images determine the tumor. As can be observed in Fig. 6, dashed lined region of the Fig. 5 is separated from the other parts using the method of color separation.

Since, middle colors are moderated, values of the elements of the array are in white and black and middle and gray points are deleted. Consequently, by counting the number of pixels available in white region, area of the tumor will be obtained.

Semantic similarity based on keywords: Conceptual unit is another main component of the proposed system. By receiving user feedbacks during retrieval, this unit performs a type of learning from the behavior of user for recognition of the meanings denoted in the image. In proposed system, conceptual unit is able to direct the cycle of retrieval in a semantic way in both modes of query and hence, its performance differs in keyword-based and image-based query. In the keyword-based query by considering initial queries and

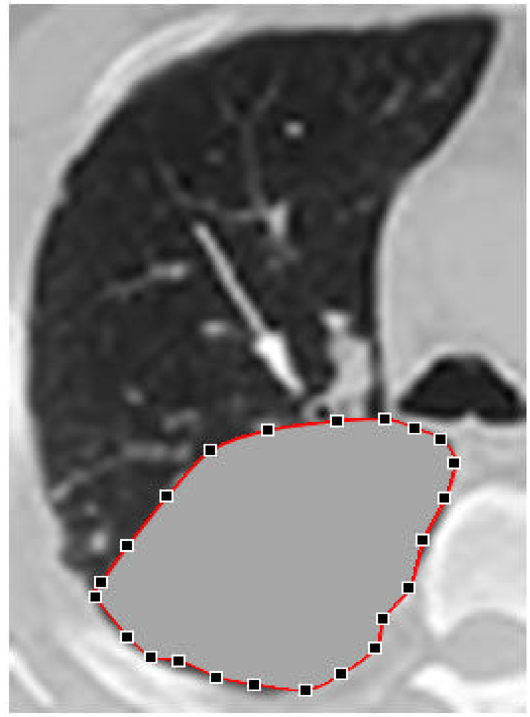

Fig. 5: The gray shape represents the margins of the tumor by using points and red line out of the area

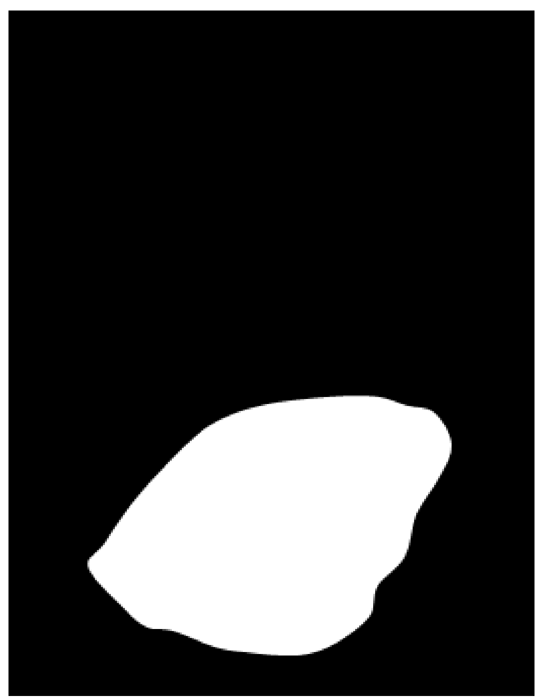

Fig. 6: Separation of tumors using the method of color separation

meaning assigned to the feedback image, conceptual unit is able to provide an absolutely semantic retrieval and also in image-based query, proposed system delegates the retrieval process after the first step which was done in content-based manner from the visual content into the semantic field. In reality, conceptual unit of the proposed system provides a more complete query which explicitly expresses the opinions of the user and as a result, conceptual unit of the proposed system enables user to have control over the process of retrieval.

The method of research in this study is, so that, after ranking images of the database based on the query of user using the method described above, images having highest ranks are shown to the user and user assigns relevant and irrelevant tags to each of them. After receiving and processing feedbacks of the user and learning from him, unit applies changes to the weight and rank relations. This process is repeated in several sessions until the user is completely satisfied. While user searches many words by assuming and between them, he in fact states that he needs images which include all given keywords. In this case, three factors contribute to the refine of the query and determination of the new value of the images of the database:

- Similarity between each image and the relevant set of images
- Similarity between each image and the irrelevant set of images
- Similarity between each image and the initial queries of the user

Positioning shows the way initial query and value of images of the database are refined according to aforesaid components when and operation is used for combination of the keywords. In this method, nearest common ancestor of two semantic nodes represents the ST between them. Indeed, the goal is to fine the ST between meaning nodes. According to this relation, the important issue in the similarity of two nodes in ST is their Nearest Ancestor (NA). It must be explained that in conditions, two semantic nodes are adapted, NA value will be equal to the maximum depth of the hierarchy. As such, relations which utilize the concept of NA can be considered as instances with the ability to compute the exact adaptation as well as ST between semantic sets. As stated earlier, principle of calculation for obtaining queries closer to user opinion relies upon the ST between keywords assigned to the feedback images and other images of the database according to keywords expressing their semantic content. The method is, so that, in image database, images are valued based on current queries and relevance feedbacks in the form of relevant and irrelevant tags assigned by the user. According to this relationship, highest level of ST is obtained between each node of the semantic nodes of image j and then average of the similarities for all images of the relevant set is evaluated for the first part of the relationship for the irrelevant set, this average is calculated as well and finally, two values are added to the similarity which represents the similarity between image j and user query. In other words, positioning calculates the ST of image j and the set of relevant and irrelevant images as well as all keywords available in initial query when using and operator.

RESULTS AND DISCUSSION

Similarity weight: Moreover, similarity weight describes the way database images are valued by their similarity level with the initial query of the user. For this purpose, default value is set equal to 0.01 which is necessary for evaluation of the semantic validity of each semantic node in image by and operation, so that, the image j can represent all meanings intended by the user if it is retrieved to present to the user. Selection of the above value as default is in accordance with experimental studies. Finally, after evaluation of all images for a more conceptual retrieval, averaging operation is necessary, so that, the score of the image be assigned based on the score of images and another retrieval be performed based on this ranking.

When a user presents many using or operation as initial query, three aforesaid factors contribute to the determination of the new value of each of the image of the database from the point of view of their adaptation to the needs of the user. Of course, in this step, comparisons are somehow different and averaging is not necessary, so that using the maximum value for all comparisons between semantic nodes, since, the query is in or mode, obtained result is demanded by the user because in this case, ST suffices even with one of the search keywords.

Relationship of similarity weight illustrates the method of refining initial query and calculation of the new value for each of the database images according to above said components when or operation is used for combination of keywords.

According to this relation, first, maximum value of ST between each node j of image k in the relevant set and semantic nodes assigned to image j of the database and then, maximum value of the obtained similarities is calculated using similarities obtained fir all semantic nodes of image k and meanings of image j. Finally, maximum value of similarity between all relevant image and image j is obtained for the first part of the relation and

Table 2: Symbols used in text

Symbol	Description
N	No. of keywords in user queries
K	No. of images of relevant set
L	No. of images of irrelevant set
I_i	Meaning i assigned to database j
K_j	Meaning j assigned to database k
L_j	Meaning j assigned to image l of irrelevant set
Q_j	Meaning j corresponding to one of the keywords
$P = \{p_1, p_2, ..., p_N\}$	Graph vertices
$A = \{a_1, a_2, ..., a_n\}$	Distance between vertices and center in normal lung
$B = \{b_1, b_2, ..., b_n\}$	Distance between vertices and center in abnormal lung
d = >R	Distance to center to calculate tumor area
C (x) = >R	Cost function
a, b, c	Triangle components, sides
s = (a+b+c)/(2)	Triangle relations
Sqrt(s(s-a)(s-b)(s-c))	Overall area
MCP(c) L.insert (All points(While (L) M←L m.distance (all_remaining_points) L.nearest_point Exit (0)	MCP algorithm
Rank 1	Value of image j
Max. depth	Maximum depth in semantic hierarchy
NA	Depth of nearest ancestors of i and j semantic sets
Node (k).value (i)	Value of image j
Node (k).value (i)	Weight of keyword i in semantic node k
Node (k). Image (j)	Relevance weight of image j with semantic node k
Weight (I) = node (k).value (i)*node (k).Image (j)	Weighting valuation
node(k).rank(sum)	Value of image j in semantic node k including a keyword
Rank (j) = node(k).rank(sum)/n	Ranking
Weight (I(= sum_k (sum_j (max ($NA_{Ii, Kj}$/Depth $_{Max}$) (Value $_{Ii}$/sum (Value $_{Ii}$)) Value $_{Kj}$/sum (Value $_{Kj}$))/m)/k-Sum_L (sum_j (max (NA $_{Ii, Kj}$/$Depth_{Max}$) (Value $_{Ii}$/sum (Value $_{Ii}$)) Value $_{Lj}$/sum (Value $_{Lj}$))/m)/L+$(i, Q)_{Similarity}$	Positioning
Similarity = score+Max (NA $_{Ii, Qi}$/Max Depth) (value $_{Ii}$/Sum $value_I$) (Q_i/Sum_{Qi}))/Num	Similarity weight
Weight (I (= Max_k (Max_j (max_i (NA $_{Ii, Kj}$/Depth $_{Max}$) (Value $_{Ii}$/sum (value $_{Ii}$)) value $_{Kj}$/sum (value $_{Kj}$)))- Max_L (Max_j (max_i (NA $_{Ii, Lj}$ /Depth $_{Max}$) (value $_{Ii}$/sum(value $_{Ii}$)) value $_{Lj}$/sum (value $_{Lj}$)))+(i, Q) $_{Similarity}$	Re weighting
(i, Q) $_{Similarity}$ = Max j (Max I (NA $_{Ii, Lj}$/Depth $_{Max}$) (value $_{Ii}$/sum (value $_{Ii}$) (Q_i/Sum_{Qi})	Similarity
Weight (I (= Max_k (Sum_j (max_i (NA $_{Ii, Kj}$/Depth $_{Max}$) (value $_{Ii}$/sum (value $_{Ii}$)) value $_{Kj}$/sum(value $_{Kj}$)/i))- Max_L (Sum_j (max_i (NA $_{Ii, Lj}$ /Depth $_{Max}$)(Value $_{Ii}$/sum (value $_{Ii}$)) value $_{Lj}$/sum (value $_{Lj}$)/i))+(i, Q) $_{Similarity}$	Valuation of input image

similarly, relation is repeated for irrelevant set. In other words, relationship is based on calculation of the value of image j with sets of relevant and irrelevant through similarity to even one of the concepts assigned to images as well as ST to even one of the keywords of query which can be effective when using or operation. In this case, for similarity, value of each of the database images with respect to their similarity to initial query of the user can be calculated using the re weighting. In Table 2 as can be seen the symbols used in this text.

Using the maximum value of the similarity weight and re weighting is because the high level of similarity between image of database and images of relevant set, irrelevant set and query suffices, since or operator is used for obtaining results.

Semantic similarity based on user image: Function of the conceptual unit of this study is similar to keyword-based query and relies upon the feedback images of the user except that in method explained previously, semantic value of the database image is evaluated according to the images of the relevant and irrelevant sets as well as the initial query while in query based on sample image, final value of the database image is obtained using sample image, final value of the database image is obtained using meanings assigned to the relevant and irrelevant sets. In this case, since, the initial query is based on the sample image, it is not possible to directly refer to keyword-based query and therefore, learning operation utilizes solely relevant and irrelevant sets. In other words, in this case, image-based query is replaced by a new query based of semantic search. In this step, two factors contribute to the determination of the new value of each image of database and ordering them:

- Value of ST of each image to relevant set
- Value of ST of each image to irrelevant set
- Valuation of the input image

According to two factors and the operation of valuating images based on ST as the nearest ancestor of semantic sets of two images, valuation of the input image represents the way conceptual unit performs for calculation of the value of each of the images of the database in image-based query. According to this relation, only meanings assigned to the relevant and irrelevant sets contribute to the valuation of the database image and hence, content similarity of the sample image and database images is less taken into account.

According to the relation, first, the maximum values of similarity between each semantic node and those of the image j of the database is found and then average of these values for all semantic nodes of the relevant image is calculated. Finally, maximum similarity between relevant images and image j is calculated as the first part of the relation. For the second part, ST of the image is investigated by the irrelevant set. In fact, according to this relation, value of each image of database is calculated based on the conceptual similarity to at least one of the images of the relevant and irrelevant sets and of course by considering all available meanings of the corresponding image.

Implementation and testing: Lung Image Database Consortium (LIDC) has a database which includes CT images of lung and information about nodules which are shown in these images including notes of 9 physicians about characteristics of nodules calcification, internal structure, level of precision, lobules, margin, sphericity coefficient, malignity and speculation.

All of these characteristics are ranked in 1-5 range with integers except calcification which is ranked in 1-6 range. Looking to the histograms of these characteristics (Fig. 7), we will find out that many of them including calcification, internal structure, precision and speculation are mainly in one or two main values. Therefore, when we try to evaluate the correlation between characteristics of image and ranking of physicians, these rankings don't help considerably.

Data were decomposed into 90 cases each of which having 100-400 DICOM images and an XML data file containing physician notes. Data were extracted from XML and centroid calculation was used for determination of images with the same nodule.

After that, nodule images were extracted from full-size CT scans of lung. In this way, DICOM files were extracted from nodules together with a set of XML files with all data corresponding to features, physicians notes and metadata for each of the nodule images.

All nodule images which were smaller than 5×5 (about 3×3 mm) were eliminated since images which are so small cannot provide meaningful data about texture (same minimum size is used by Kim *et al.* (2002).

After elimination of these images and those having numerous lines, final database included 2424 images from 141 unique nodules. Average size of images is 15×15 pixels and actual average size of the image is about 10×10 mm. Smallest nodules are about 3×3 mm while largest size is more than 70×70 mm. The 88% of the images are 20×20 mm.

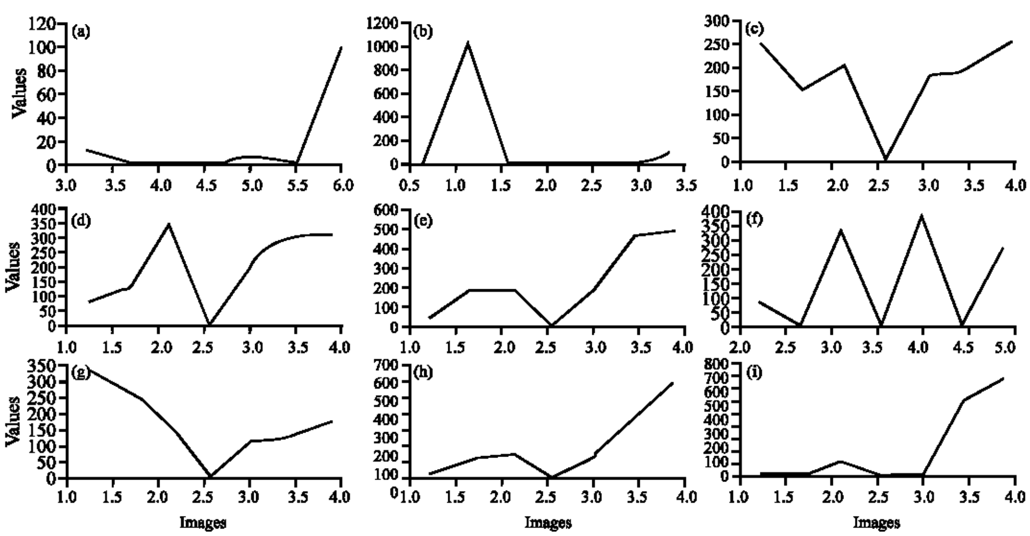

Fig. 7: Histogram of images; a) Calculation; b) Internal structure; c) Lobulation; d) Maligancy; e) Marin; f) Sphericity; g) Spiculation; h) Subtlety and i) Texture

User interface was written in C# and .NET framework and started as a simple viewer for study of the image and then, it was extended for comparison of two images along with each other. After that, calculation of the distance in feature vector was added as a way for evaluation of the similarity between images.

As next step, a CBIR program which allows user to select a query image and a threshold. Then, program analyzed all of the images and applies similarity criteria and determines the closest image to the query image. All images which have distance exceeding the threshold are cancelled out and then, remaining images are ranked from closest image to query image to farthest image with respect to query image. This interface also allows users to select a texture description which has the vector of features.

Figure 8 shows that when we change some of the retrieved items, Gabor and Markov function in a relatively same manner and when an item is retrieved, best average precision is about 88%. Figure 7 also shows that when the number of retrieved images is <5, Markov has a function similar to Gabor. However, if 5 and 10 images are retrieved, Gabor shows significant improvement compared to Markov. When retrieving an item, co-occurrence matrixes with average precision as much as 29% perform considerably better than Gabor and Markov. A probable explanation for it is that co-occurrence model encodes texture information in a global level while both Gabor and Markov are calculated in pixel level.

Tests performed in this step for keyword-based query are for both cases of applying and and or operations and of course random selection of the keywords. At the beginning of query, usesr enters keywords and in each stage of retrieval, presents his opinions in the form of relevance feedback as “relevant” and “irrelevant”. Similarly, for content-based search user first selects images as sample for query and then, continues his interaction with system through feedback of the images as “relevant” and “irrelevant”. In both cases, user repeats interaction stages until achieving satisfaction from retrieval results. It must be noted that ST structure is a dynamic structure with the ability to extend in the form of synonym keywords and in a more general form in various semantic fields and hence, it will be possible to use the proposed system with databases with different semantic concepts.

Figure 9 illustrates a schematic of the proposed system of retrieval in responding to keyword-based query with “asthma” as query. In this way, Fig. 9 illustrates the schematic of the proposed system in query mode based on the sample image.

In this case, images are retrieved based on content query and in the form of visual similarity with the query image.

In this system, user starts another semantic retrieval. In performed tests, random query is evaluated in two query modes by keyword with or and and operators as well as query with sample image for both semantic and content searches for interaction with user.

In this step, according to the aim of the system of image retrieval including presenting semantic retrievals and satisfying users about their asked meanings. Tests are performed in the form of meaning and visual content of images for showing the efficiency of the aforesaid system in the form of meaning. In other words, expression of the performance of the proposed system in case it is started by keyword-based query and continues in absolutely semantic form by referring to meanings

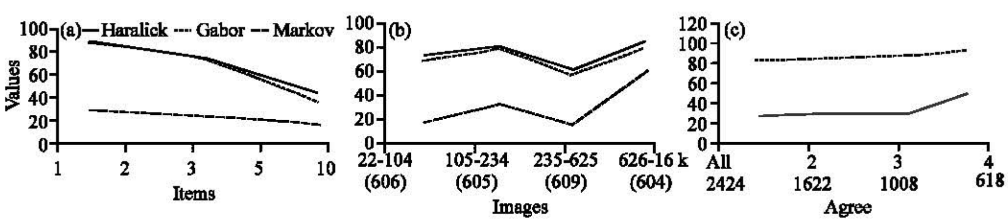

Fig. 8: Investigation of the retrieval algorithm; a) Image retrived; b) Images size and c) Matching texture rating

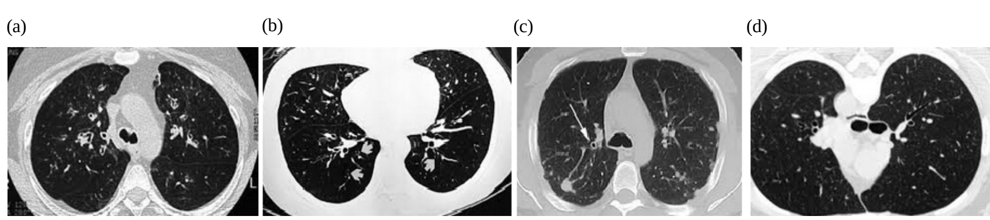

Fig. 9: System of image retrieval in query mode based on keyword

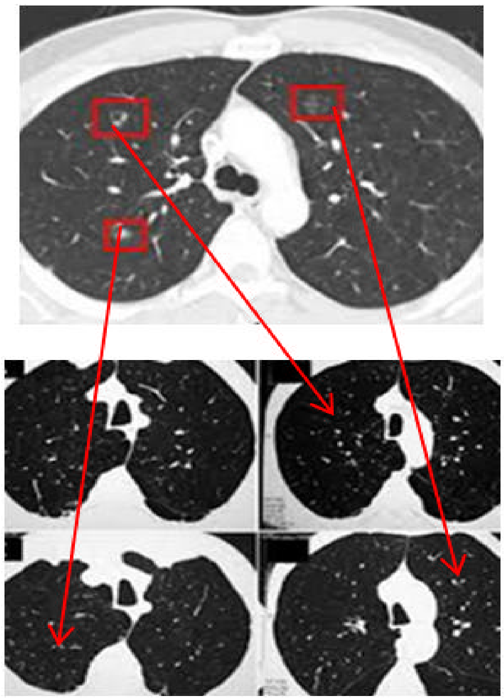

Fig. 10: System of image retrieval in query mode based on images. The top image is query image and the others are similar image based on top image. The red lines show the place of nodules in different images

corresponding to feedback images through conceptual unit is compared to another state of the system started with a visual query and then, shifted by conceptual unit from image context and low-level visual content to meaning context through relevance feedback of the user (Fig. 10).

Figure 10, system of image retrieval in query mode based on images. The top image is query image and the others are similar image based on top image. The red lines show the place of nodules in different images.

For the sake of comparison of two methods of classification and change of the color, precision is measured. For this end, areas calculated by two methods are compared and results are shown in Fig. 11 and 12. For calculation of the error of the method, table of symbols is used.

This difference is due to limited number of points taken in first method as graph vertices. As number of points increase and distances of the selected points decrease, area will be calculated more precisely. Of course, as can be seen in Fig. 12 as the size of the tumor increases, precision increases accordingly. This algorithm performs well in low level of noises and doesn't need

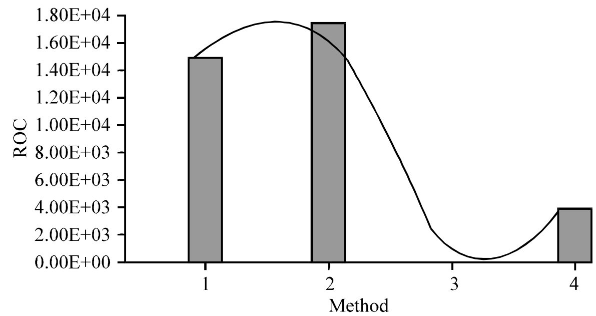

Fig. 11: ROC for both methods

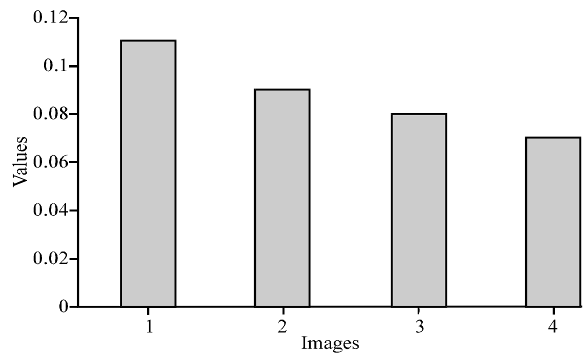

Fig. 12: Results of the proposed method for four sample images

large memories and it is so fast that, it can be used in health care centers and its precision exceeds 90%. ROC diagram is represented in Fig. 11. It is evident that diagram corresponding to the first method is more uniform which shows its superiority and normality of the proposed method.

For completing the comparison of the meaning-based retrieval and visual content of the images, performance of the system is compared to the case of content-based search. In this case, after retrieval of the images based on characteristics of the low-level of color, next stages of the interaction continue without taking into account the meanings listed in feedback images like systems based on content. According to results, precision of the proposed system can be represented in several stages of the semantic retrieval for all three cases in Fig. 13.

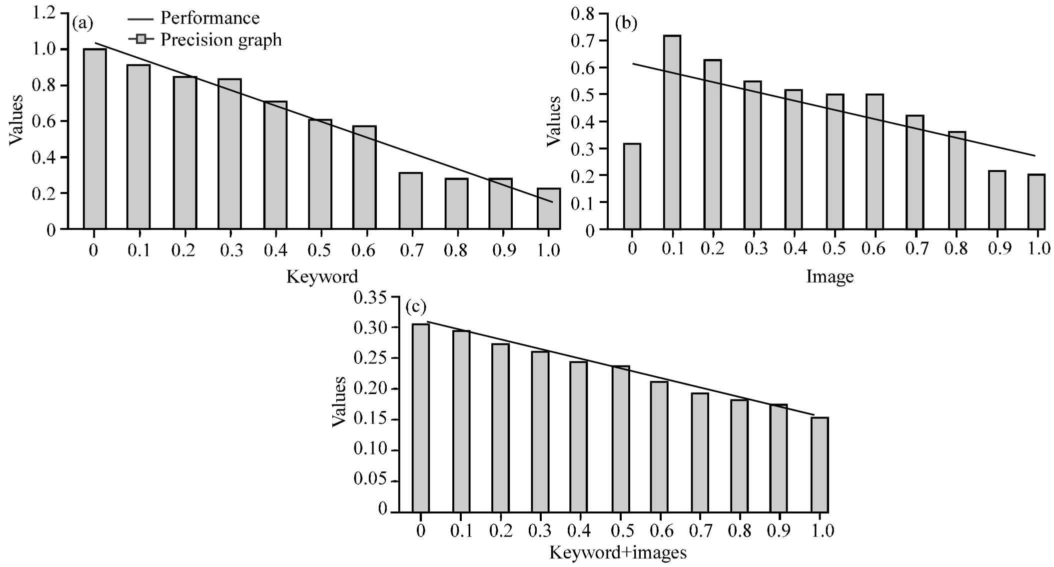

Fig. 13: Precision recall diagram of the proposed system performance of the system is better in keyword-based query; a) Used keyword query; b) Used image query and c) Used keyword+image query

As can be seen in keyword-based query, proposed method has an acceptable performance in image retrieval and in image-based query, due to low precision of the content search for semantic retrieval of the image, precision of retrieval in presented precision recall diagram is in a low level in the first step and in next steps for retrieval of images based on semantic search, precision increases. While for other parts of the diagram illustrating the function of the content-based retrieval systems and is assigned to the visual query and content processing operation for next stages of the interactive retrieval, precision recall diagram illustrates the unreliability of the content-based search for semantic retrieval of images.

In other words, in the case of keyword-based query, as a result of semantic referral to query in the form of words, performance of the system in all retrieval stages yields more precision compared to image-based retrieval and also in the image-based query, repetition of the stages based on meanings available in feedback images will yield better results compared to content-based search using visual features of feedback images.

As can be seen in Fig. 13, performance of the system is better in keyword-based query compared to image-based query. According to diagrams, precision and recall of the proposed system with respect to the number of retrieved images during an interactive retrieval session for keyword-based query is in an acceptable level. Moreover, for query based on sample image which initially presents an image as query request and therefore, reduces the precision of the semantic retrieval due to nature of low-level visual features having no meaning about the image, precision and recall diagrams of the proposed system are in lower level compared to results obtained for keyword-based query.

It must be noted that according to tests, performance of the system is acceptable in presenting a semi-automatic way for semantic retrieval of the images using ST including high-level concepts in meaning and shifting image to meaning.

CONCLUSION

Since, understanding the opinion of users about results of the systems of retrieval is of great significance, a method is presented in this study which processes the opinion of the user in each stage of retrieval in an interactive manner and provides another query based on the opinion of the user in each stage. Processing function of the system is presented under the conceptual unit which extracts the meanings intended by user from his feedbacks by performing a short-term learning operation during each interactive session and starts another semantic retrieval.

Proposed system utilizes a hierarchical ST in the set of synonyms including high-level concepts such as facial expressions and personality traits of the human and during each learning step, it calculates the ST of images for more conceptual retrievals in two cases or and for keyword-based query for images described as relevant and irrelevant. In addition, proposed system in image-based query replaces content search of images with semantic search based on ST with feedback images and after retrieval of the initial results for next steps of interactive retrieval. In reality, proposed system meets semantic needs of users in a case image-based and keyword-based query in a high-level and conceptual way when learning is performed without considering low-level visual features and solely based on semantic content of images. In this way, it is capable of shifting search from content to semantic context. Results of implementation show an acceptable precision for this system, so that, under the function of conceptual unit, obtained results by content and keyword-based query are more meaningful compared to query based on sample image and content search operation and yields better results.

Owing to the importance of on-time diagnosis of lung cancer, a new method based on CT images processing is introduced which is conducted in three stages. In first step using the method of graphing, location and area of the tumor are determined. This stage is accomplished by the knowledge of the expert and in a manual way. However, it can be automated using neural networks and genetic algorithm in future works. In next stage using the image processing method, location of tumors are recognized and determined and they are completely separated from other parts of the image and then, area of the separated part is calculated. In final step, results of two methods are compared and precision of the research is evaluated.

Presented method is very effective in reduction of the human errors in diagnosis of tumors in images. Various images received by the presented model were investigated and analyzed and their results highlight considerable improvement in precision and speed and results are compared with the position diagnosed by radiologist and expert as well, thereby the software performs the diagnosis of tumors with a very satisfactory precision (>90%) in CT images.

RECOMMENDATIONS

In future researches, it will be attempted to automate the stage of detection of points in graph and creation of better graph to improve the accuracy and reduce the error along with reduction of the role of human.

REFERENCES

Agarwal, S., A.K. Verma and P. Singh, 2013. Content based image retrieval using discrete wavelet transform and edge histogram descriptor. Proceedings of the 2013 International Conference on Information Systems and Computer Networks (ISCON), March 9-10, 2013, IEEE, Mathura, India, ISBN:978-1-4673-5987-0, pp: 19-23.

Antani, S., D.J. Lee, L.R. Long and G.R. Thoma, 2004. Evaluation of shape similarity measurement methods for spine X-ray images. J. Visual Commun. Image Represent., 15: 285-302.

Balmashnova, E., B. Platel, L. Florack and T.H.B.M. Romeny, 2007. Content-based image retrieval by means of scale-space top-points and differential invariants. Proceedings of the MICCAI International Workshop on Medical Content-Based Image Retrieval for Biomedical Image Archives: Achievements, Problems and Prospects, October 29November-2, 2007, MICCAI, Brisbane, Queensland, Australia, pp: 83-92.

Bansal, R., L.H. Staib, D. Xu, H. Zhu and B.S. Peterson, 2007. Statistical analyses of brain surfaces using Gaussian random fields on 2-D manifolds. IEEE. Trans. Med. Imaging, 26: 46-57.

Borji, A. and L. Itti, 2012. Exploiting local and global patch rarities for saliency detection. Proceedings of the 2012 IEEE International Conference on Computer Vision and Pattern Recognition (CVPR), June 16-21, 2012, IEEE, Providence, Rhode Island, USA., ISBN:978-1-4673-1226-4, pp: 478-485.

Borji, A. and L. Itti, 2013. State-of-the-art in visual attention modeling. IEEE. Trans. Pattern Anal. Mach. Intell., 35: 185-207.

Brahmi, D. and D. Ziou, 2004. Improving CBIR systems by integrating semantic features. Proceedings of the 1st Canadian International Conference on Computer and Robot Vision, May 17-19, 2004, IEEE, London, Ontario, Canada, pp: 233-240.

Carneiro, G. and N. Vasconcelos, 2005b. A database centric view of semantic image annotation and retrieval. Proceedings of the 28th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, August 15-19, 2005, ACM, New York, USA., pp: 559-566.

Carneiro, G. and N. Vasconcelos, 2005a. Formulating semantic image annotation as a supervised learning problem. Proceedings of the IEEE Computer Society International Conference on Computer Vision and Pattern Recognition Vol. 2, June 20-25, 2005, IEEE, San Diego, California, USA., ISBN:0-7695-2372-2, pp: 163-168.

Carneiro, G., A.B. Chan, P.J. Moreno and N. Vasconcelos, 2007. Supervised learning of semantic classes for image annotation and retrieval. IEEE. Trans. Pattern Anal. Mach. Intell., 29: 394-410.

Cauvin, J.M., L.C. Guillou, B. Solaiman, M. Robaszkiewicz and L.P. Beux *et al*., 2003. Computer-assisted diagnosis system in digestive endoscopy. IEEE. Trans. Inf. Technol. Biomed., 7: 256-262.

Chaturvedi, N., S. Agarwal and P.K. Johari, 2014. A novel approach of image retrieval based on texture. Intl. J. Enhanced Res. Manage. Comput. Appl., 3: 42-48.

Comaniciu, D., P. Meer and D.J. Foran, 1999. Image-guided decision support system for pathology. Mach. Vision Appl., 11: 213-224.

Doyle, S., M. Hwang, S. Naik, M. Feldman and J. Tomaszeweski *et al*., 2007. Using manifold learning for content-based image retrieval of prostate histopathology. Proceedings of the 2007 MICCAI International Workshop on Content-Based Image Retrieval for Biomedical Image Archives: Achievements, Problems and Prospects, October 29-Novembeb 2, 2007, MICCAI, Brisbane, Queensland, Australia, pp: 53-62.

Figueiredo, M.A.T., A. Vailaya, A.K. Jain and H.J. Zhang, 2001. Image classification for content-based indexing. IEEE Trans. Image Processing, 10: 117-130.

Gevers, T. and A.W. Smeulders, 2004. Content-Based Image Retrieval: An Overview. In: Emerging Topics in Computer Vision, Medioni, G. and S.B. Kang (Eds.). Prentice Hall, Upper Saddle River, New Jersey, USA., pp: 52-52.

Gletsos, M., S.G. Mougiakakou, G.K. Matsopoulos, K.S. Nikita, A.S. Nikita and D. Kelekis, 2003. A computer-aided diagnostic system to characterize CT focal liver lesions: Design and optimization of a neural network classifier. IEEE Trans. Inform. Technol. Biomed., 7: 153-162.

Golland, P., W.E.L. Grimson, M.E. Shenton and R. Kikinis, 2005. Detection and analysis of statistical differences in anatomical shape. Med. Image Anal., 9: 69-86.

Guld, M.O., C. Thies, B. Fischer and T.M. Lehmann, 2005. Content-Based Retrieval of Medical Images by Combining Global Features. In: Accessing Multilingual Information Repositories, Peters, C. (Ed.). Springer, Berlin, Germany, pp: 702-711.

Hentschel, C., A. Nurnberger, I. Schmitt and S. Stober, 2006. Safire: Towards Standardized Semantic Rich Image Annotation. In: Adaptive Multimedia Retrieval, Marchand-Maillet, S., E. Bruno, A. Nurnberger and M. Detyniecki (Eds.). Springer, Berlin, Germany, ISBN:978-3-540-71544-3, pp: 12-27.

Hill, P., A. Achim and D. Bull, 2012. The undecimated dual tree complex wavelet transform and its application to bivariate image denoising using a cauchy model. Processing of the 2012 19th IEEE International Conference on Image, September 30-October 3, 2012, IEEE, Orlando, Florida, USA., ISBN:978-1-4673-2534-9, pp: 1205-1208.

Huang, H.K., J.F. Nielsen, M.D. Nelson and L. Liu, 2005. Image-matching as a medical Diagnostic Support Tool (DST) for brain diseases in children. Computerized Med. Imaging Graphics, 29: 195-202.

Hyvonen, E., M. Salminen and M. Junnila, 2004. Annotation of heterogeneous database content for the semantic web. Proceedings of the 4th International Workshop on Knowledge Markup and Semantic Annotation (SemAnnot 2004), November 8, 2004, University of Helsinki, Hiroshima, Finland, pp: 1-10.

Ion, A.L., L. Stanescu and D. Burdescu, 2007. Semantic based image retrieval using relevance feedback. Proceedings of the 2007 EUROCON International Conference on Computer as a Tool, September 9-12, 2007, IEEE, Warsaw, Poland, ISBN:978-1-4244-0812-2, pp: 303-310.

Kwak, D.M., B.S. Kim, O.K. Yoon C.H. Park and J.U. Won *et al*., 2002. Content-Based ultrasound image retrieval using a coarse to fine approach. Ann. New York Acad. Sci., 980: 212-224.

Laaksonen, J., M. Koskela, S. Laakso and E. Oja, 2001. Self-organising maps as a relevance feedback technique in content-based image retrieval. Pattern Anal. Appl., 4: 140-152.

Lim, J.H. and J.P. Chevallet, 2005. Vismed: A Visual Vocabulary Approach for Medical Image Indexing and Retrieval. In: Information Retrieval Technology, Geunbae, G.L., Y. Akio, M. Helen and H.M. Sung (Eds.). Springer, Berlin, Germany, ISBN:978-3-540-29186-2, pp: 84-96.

Liu, G.H. and J.Y. Yang, 2013. Content-based image retrieval using color difference histogram. Pattern Recognit., 46: 188-198.

Lu, Y., C. Hu, X. Zhu, H. Zhang and Q. Yang, 2000. A unified framework for semantics and feature based relevance feedback in image retrieval systems. Proceedings of the 8th ACM International Conference on Multimedia, October 30, 2000, ACM, New York, USA., pp: 31-37.

Lubbers, K., D.A.P. Vries, T. Huibers and V.D.P. Vet, 2004. A Probabilistic Approach to Medical Image Retrieval. In: Multilingual Information Access for Text, Speech and Images, Peters, C., P. Clough, J. Gonzalo, G.J.F. Jones and M. Kluck *et al* (Eds.). Springer, Berlin, Germany, ISBN:978-3-540-27420-9, pp: 761-772.

Mao, J. and A.K. Jain, 1992. Texture classification and segmentation using multiresolution simultaneous autoregressive models. Pattern Recognition, 25: 173-188.

Muller, H., W. Muller, D.M.G. Squire, S. Marchand-Maillet and T. Pun, 2001. Performance evaluation in content-based image retrieval: Overview and proposals. Pattern Recog. Lett., 22: 593-601.

Panagi, P. and S. Dasiopoulou, 2006. A learning approach to semantic image analysis. Proceedings of 2nd International Conference on Mobile Communications, September 18-20, 2006, ACM, Alghero, Italy, pp: 1-6.

Petrakis, E.G., K. Kontis, E. Voutsakis and E.E. Milios, 2006. Relevance feedback methods for logo and trademark image retrieval on the web. Proceedings of the 2006 ACM International Symposium on Applied Computing, April 23-27, 2006, ACM, New York, USA., ISBN:1-59593-108-2, pp: 1084-1088.

Pokrajac, D., V. Megalooikonomou, A. Lazarevic, D. Kontos and Z. Obradovic, 2005. Applying spatial distribution analysis techniques to classification of 3D medical images. Artif. Intell. Med., 33: 261-280.

Puviarasan, N., R. Bhavani and A. Vasanthi, 2014. Image retrieval using combination of texture and shape features. Intl. J. Adv. Res. Comput. Commun. Eng., 3: 5873-5877.

Qian, X. and H.D. Tagare, 2005. Optimal Embedding for Shape Indexing in Medical Image Databases. In: Medical Image Computing and Computer-Assisted Intervention, Duncan, J.S. and G. Gerig (Eds.). Springer, Berlin, Germany, ISBN:978-3-540-29326-2, pp: 377-384.

Rahman, M.M., P. Bhattacharya and B.C. Desai, 2007. A framework for medical image retrieval using machine learning and statistical similarity matching techniques with relevance feedback. IEEE. Trans. Inf. Technol. Biomed., 11: 58-69.

Sasso, G., H.R. Marsiglia, F. Pigatto, A. Basilicata and M. Gargiulo *et al*., 2005. A visual query-by-example image database for chest CT images: Potential role as a decision and educational support tool for radiologists. J. Digital Imaging, 18: 78-84.

Shah-Hosseini, A., 2007. Semantic image retrieval using relevance feedback and transaction logs. Ph.D Thesis, Louisiana State University, Baton Rouge, Louisiana.

Shevade, B. and H. Sundaram, 2003. Vidya: An experiential annotation system. Proceedings of the 2003 ACM SIGMM International Workshop on Experiential Telepresence, November 7, 2003, ACM, New York, USA., pp: 91-98.

Shyu, C.R., C.E. Brodley, A.C. Kak, A. Kosaka and A.M. Aisen *et al*., 1999. ASSERT: A physician-in-the-loop content-based retrieval system for HRCT image databases. Comput. Vision Image Understanding, 75: 111-132.

Smeulders, A.W.M., M. Worring, S. Santini, A. Gupta and R. Jain, 2000. Content-based image retrieval at the end of the early years. IEEE Trans. Patt. Anal. Mach. Intel., 22: 1349-1380.

Toews, M. and T. Arbel, 2007. A statistical parts-based model of anatomical variability. IEEE. Trans. Med. Imaging, 26: 497-508.

Wang, Y. and W. Zhang, 2012. Coherence vector based on wavelet coefficients for image retrieval. Proceedings of the 2012 IEEE International Conference on Computer Science and Automation Engineering (CSAE) Vol. 2, May 25-27, 2012, IEEE, Zhangjiajie, China, ISBN:978-1-4673-0088-9, pp: 765-768.

Wenyin, L., S.T. Dumais, Y. Sun, H. Zhang and M. Czerwinski *et al*., 2001. Semi-Automatic Image Annotation. In: Human-Computer Interaction, Michitaka, H. (Ed.). IOS Press, Amsterdam, Netherlands, pp: 326-333.

Xu, Z., X. Xu, K. Yu and V. Tresp, 2003. A Hybrid Relevance-Feedback Approach to Text Retrieval. In: Advances in Information Retrieval, Sebastiani, F. (Ed.). Springer, Berlin, Germany, ISBN:978-3-540-01274-0, pp: 281-293.

Yang, J., L. Wenyin, H. Zhang and Y. Zhuang, 2001. Thesaurus-aided approach for image browsing and retrieval. Proceedings of the ICME 2001 IEEE International Conference on Multimedia and Expo, August 22-25, 2001, IEEE, New York, USA., pp: 1135-1138.

Zhu, H., B.G. Goodyear, M.L. Lauzon, R.A. Brown and G.S. Mayer *et al*., 2003. A new local multiscale Fourier analysis for medical imaging. Med. Phys., 30: 1134-1141.

Zhu, X., W. Liu, H. Zhang and L. Wu, 2000. Image retrieval and semiautomatic annotation scheme for large image databases on the web. Proceedings of the International Conference on Internet Imaging II Vol. 4311, December 27, 2000, SPIE, San Jose, California, USA., pp: 168-178.