A Review On Biomedical Image Retrieval

Megha A. Mandwe

Abstract-This review paper presents content based image retrieval algorithms in biomedical domain. CBIR was proposed in early 1990's which uses visual contents of image such as color, texture, shape features as the image index for image retrieval, with advancement of imaging, clinical imaging significantly impacted with improved image handling. This paper also gives overview of user interactive approach of relevance feedback technique for efficient image retrieval. Today's various CBIR systems for medical image involves steps from database image, query image, use of machine learning approach for categorization and prefiltering of images to reduce search space e.g. SVM training retrieval is based on Image feature representation, similarity matching. Probabilities output from the SVM are used to filter out irrelevant images before similarity matching.

The goal of CBIR is not only to replace text based image retrieval but to complement them with visual tools of searching. Image retrieval using various tools like CBIR plays important role as far as research, teaching, diagnoses and treating a disease is concerned.

Index terms: Content Based Image Retrieval (CBIR), Medical imaging, Image Retrieval, Support vector machine (SVM), Similarity matching

1. INTRODUCTION

Since 1990's Content Based Image Retrieval has been an active and fast advancing research area, a technique which uses visual contents to search images from large scale image databases according to users interests.

A digital imaging revolution over the past three decades has changed medical domain a lot. In recent years rapid advances of software and hardware technology have eased the training, research, teaching regarding problems in maintaining large medical image collections. As images are important source of diagnoses, medical research and education, its significant challenge is to search images in large collections as medical images differ significantly from other general purpose images. There are digital images of diverse modalities being produced using sophisticated image acquisition devices in hospitals and medical centers. Search results in medical images can be improved by combining text based search with visual features computed directly on image content called as content based image retrieval (CBIR).

This paper is organized in six subsections. The subsequent section explains important aspect of Content Based Image Retrieval in early years. Section III different techniques used for image retrieval and study of algorithms used for retrieval. Section IV is wide description of review of earlier retrieval system.

2. IMPORTANT ASPECT OF CBIR

In small collection of image image retrieval is easy with simply browsing but this is not the case with large databases. Image retrieval problem is the searching relevant images in large database that are relevant to users query image. CBIR system uses visual contents such as color, texture, shape features as image index for image retrieval. The effectiveness of CBIR system is measured mainly by two parameters from information retrieval such as precision and recall which are described as follows

Precision: Precision the number of relevant images returned to the total number of images returned.

$$precision = \frac{no.relevant\ images\ retrieved}{no.images\ retrieved}$$

A high precision means less percentage of irrelevant images in the retrieval i.e .few false alarms.

Recall: Recall is the number of relevant images returned to the total number of images.

$$Recall = \frac{no.relevant\ images\ retrieved}{no.relevant\ images}$$

A high recall means less percentage of failure of relevant images to be retrieved.

Another factor for the success of the CBIR system is the feature representation which is described as follows.

3. TECHNIQUES IN IMAGE RETRIEVAL

The overall success of image retrieval technique is depends on various factors like feature representation, indexing technique, learning technique used i.e classifier used in classification technique.

As CBIR uses visual contents for retrieval these visual contents are stored as mainly three leves which are as follows

Low level: It includes features such as color, texture, shape

Middle level: It includes presence of objects

High level: It includes impressions concerned with objects

3.1 Image feature representation:

As defined in earlier sections features at different levels are represented as feature vector. Specifically low level features color, edge . Based on MPEG standard CLD, EHD are extracted. CLD is compact spatial distribution of color. CLD extraction process contains four steps as Image partitioning, representative color selection, DCT transformation, zigzag scanning. While EHD represent local edge distribution in image in various types, vertical, horizontal, 45° diagonal, 135° diagonal and non directional edges and histogram with 80) bins is obtained.

3.2 Multiclass SVM:

Basically SVM is binary classifier, a multiclass SVM combines all pairwise comparisons or one against one . Multiclass SVM uses K(K-1)/2 binary classifiers to separate K mutually exclusive classes.

Multiclass SVM is one of the advance techniques in supervised learning technique. It has two stages training and testing. Classification problem is to assigning each image to predefined K classes. This retrieval using includes steps as shown in fig(2)

Each image I_j is divided and labeled with concept labels as

$\{ X_{1j}, \ldots, X_{2j}, \ldots, X_{lj}\}$ each X_{kj} is a color and texture vector.

$$P_i\ k_j = P(y = i|X_{kj}), 1 \leq j \leq L \qquad (1)$$

The initial input to the system is the feature vector set of the patches along with their manually assigned corresponding concept labels. Images in the dataset are annotated with the concept labels by fixed partitioning each image I_j into l regions as $\{ X_{1j}, \ldots, X_{2j}, \ldots, X_{lj}\}$ where each $X_{1j} \in \Re^d$ is a combined color and texture feature vector. For each X_{kj} , the concept probabilities are determined by the prediction of the multiclass SVMs

$$\boldsymbol{f_j^{concept}} = [w_{1j}, \ldots, w_{ij}, \ldots, w_{Lj}]^T \qquad (2)$$

Where each w_{ij} denotes the weight of a concept c_i, $1 \leq i \leq L$ in image I_j, depending on its information content.

$$p_m = P(y = w_m \mid X)\ for\ 1 \leq m \leq M \qquad (3)$$

The multiclass finds the probability or confidence at each category as in equation 1 where each image is manually annotated with a single category label selected out of M categories. So a set of M labels are defined as $\{w_1, \ldots, w_i, \ldots w_m\}$ where each w_i characterizes the representative image category at global level.

$$p_j = [\, p_{j1}, \ldots, p_{jm}, \ldots p_{jM}]^T \qquad (4)$$

Here, p_{jm} , $1 \leq m \leq M$, denotes the probability or class confidence score that an image I_j belongs to the category w_m in terms of the feature vectors based on applying early or late fusion strategies for classification.

$$Sim(I_q, I_j) = \sum_F \alpha^F S^F (I_q, I_j) \qquad (5)$$

The similarity between a query image I_q and target image I_j is described as in equation 5 Where $F \in \{\text{Concept}, \text{Keypoint}, \text{EHD}, \text{CLD}, \text{CEDD}, \text{FCTH}\}$ and $S^F(I_q, I_j)$ are the similarity matching function (generally Euclidean) in individual feature spaces and α^F are weights

$$E = \frac{\sum_{i=1}^{K} Rank(i)}{K/2} * P(K) \qquad (6)$$

For each ranked list based on individual similarity matching, we also consider top K images and measure the effectiveness as in equation 6 where $Rank(i)$= 0 if image in the rank position i is not relevant based on user's feedback and $Rank(i)$= $(k-i)/(K-1)$ for the relevant images. Hence, the function $Rank(i)$ monotonically decreasing from 1 (if the image at rank position 1 is relevant) down to zero (e.g., for a relevant image at rank position K).

Fig (2) shows block diagram of classification driven image retrieval when search and similarity matching is performed on pre-filtered dataset.

Fig (3) shows flow of algorithms in classification drven image retrieval system where results are refined with the help of relevance feedback. Algorithms in classification driven retrieval system can be summarized as follows.

Table 1 shows comparative analysis of algorithms used for classification based image retrieval.

Algorithm1: Image Filtering

- ***Select set of training images of predefined categories for SVM learning.***

- *Store category vectors of database images as category index.*
- *Determine category vector for query image*
- *Candidate images of query images are selected for further similarity matching*

Algorithm 2: Similarity Fusion

- *Store category specific feature weights for similarity matching.*
- *Calculate individual feature vector for query image.*
- *For each feature get category prediction depending on probabilistic output of SVM*
- *Get final category of query image.*
- *Consider the individual feature weight for query image.*
- *Combine the similarity score in linear combination with feature weight.*
- *Return top ranked images in descending order of similarity matching score.*

Algorithm 3: RF based similarity fusion

- *Initially consider top ranked images based on similarity fusion on an equal feature weighting*
- *Obtain the users feedback about relevant images from top K images*
- *Calculate new query vector as mean vector of relevant images.*
- *Measure effectiveness for each ranked list based on similarity matching*
- *Normalize the effectiveness*
- *Consider normalize score as updated weights*

3.3 CLUSTERING:

Clustering is unsupervised classification technique where in feature vectors are classified on the basis of their similarity.
The FCM is most widely used clustering algorithm. The FCM function is given by

$$J_{FCM}(\text{ w, V:Z})=\sum_{i=1}^{N}\sum_{j=1}^{c} w_{ji}^{m} \text{ dist } (z_i, v_j)$$

Where z is finite set of unlabeled feature vectors, c is the number of clusters. V is the prototype where wji is the membership degree of feature zi to the j^{th} cluster. dist (z_i, v_j) is similarity function expressed by Euclidean or Mahalanobis distance.
In[6] Fuzzy c-mean clustering technique is used in classification. In Fuzzy clustering feature vector is assigned with degrees of membership. Fuzzy c-mean algorithm can be summarized as.
FCM algorithm:

- *Initialize the cluster number*
- *Select cluster centers*
- *Select features and calculate initial membership degrees*
- *Update all new cluster centers*
- *Update membership degree with new similarity matching with respect to new cluster centers*

ISSN 2229-5518

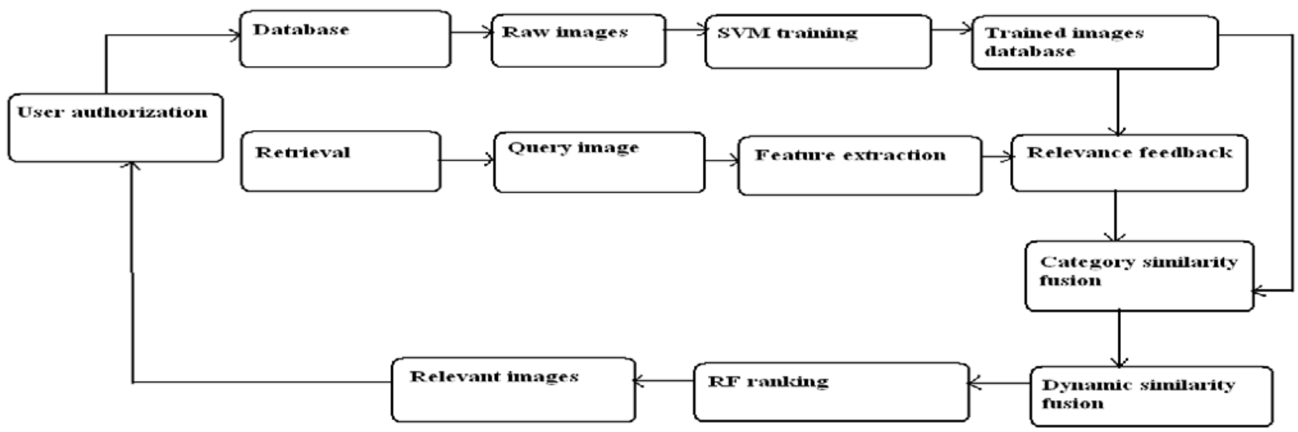

Figure 1 Flow diagram of classification driven image retrieval system

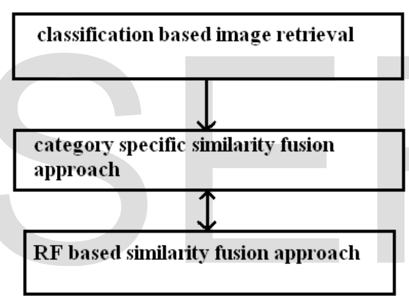

Figure 2 Flow of algorithms

Table 1 Comparative analysis of classification based retrieval techniques algorithms

CLASSIFICATION BASED IMAGE RETRIEVAL	CATEGORY SPECIFIC SIMILARITY FUSION APPROACH	RF BASED SIMILARITY FUSION
In this approach author has utilize the information about category prediction of query and database images for image filtering.	In this approach for a query image its category at a global level is determined by employing the SVM learning	In this approach user can refine the search process with option such as RF.
The main problem with this approach is that all features will have hard coded or fixed weight similarity matching approach	Instead of using the predetermined fixed weight bases approach the precomputed category specific feature weights based on the online category specific feature weights based on online category prediction are utilized	In this approach updation of feature weights is performed by similarity matching based on equal equal weighting to provide a feedback about the relevant images from the top k returned images.

4. RELATED WORK

C. R. Shyu et.al[1] have introduced ASSERT(Automatic Search and Selection Engine with Retrieval Tools) system for HRCT(High Resolution Computed Tomographic) images in which global characterization alone cannot lead to satisfactory retrieval results due to variation in gray level in highly localized regions. Where they have introduced a human in the loop approach in which the human delineates the pathology bearing regions (PBR) and a set of anatomical landmarks in the image when the image is entered into the database. Still high data entry cost, and this system is restricted to High Resolution Computed Tomography images of lungs are some of the drawbacks of ASSERT system. As HRCT images have complex structure and different regions as inside and outside lung boundary are considered and categories are determined based on their orientation and then respective attributes are considered.

Thomas M. Lehmann et.al[2] has given A novel multistep approach for CBIR which is similar to Blobworld project.IRMA (Image Retrieval in Medical Application) performs image retrieval in seven steps which are as follows

Categorization: This step determines image modality at global level and its orientation. It considers reference database and image is selected and classified by arbitrarily by radiologists.

Registration: It is related with prototype which is member of category and is done by user.

Feature Extraction: Image descriptors are obtained for each pixel.

Feature selection: It combines knowledge of query and database image category.

Indexing: Image is maked by user at the time of querying as Region of interest and it is represented by different blobs and respective graphs.

Identification: Blobs formed in indexing are linked in identification process. Relationship between different blobs is determined according to prototype given by user.

Retrieval: It is process based on identified blobs.

IRMA is considered as method in which features are transformed in value , pixel or tree data. IRMA is used with central database as well as with distributed database hence it provides different transperencies.

SPIRS(Spine Pathology and Image Retrieval System) provides hybrid visual and text queries which is based on multiple partial shape matching and iterative querying. It has used only visual contents for retrieval and accuracy has been increased with the use of relevance feedback. It can be useful with whole as well partial shape match which is very useful for complex structure of medical images.Hsu et.al has given image retrieval approach which is hybrid based on image and text query.

Supporting text is given input to database and imaging data is given to segmentation algorithm after segmentation feature extraction is performed and indexing is applied on extracted features these results are combined with stored database images features. Here partial shape matching is also performed if ROI is concerned by user.

Rui et.al[12] has given concept of relevance feedback. Relevance feedback which is concept taken from information retrieval and interactive approach in CBIR. Relevance Feedback takes into account the two major characteristics of CBIR i.e the gap between high level concepts and low level features. Three main properties of relevance feedback which are advantageous over computer centric approach are as follows:

- Multimodality
- Interactivity
- Dynamic

Retrieval based on object model in[12] can be summarized as follow:

- Objects (O)
- Features(f1…..,fi)
- Representations{(r11,r1j),(ri1,rij)}
- SimilarityMeasures{(W11k,W1jk),(Wi1k,Wijk)}
- Representations{(r11,r1j),(ri1,rij)}
- Features(f1…..,fi)
- Queries(Q)

Unlike computer centric approach relevance feedback allows to update feature weights dynamically according to user's information.

Retrieval process is summarized as follows:

- ***Initialize weights***
- ***User's information need is distributed among different features***
- ***User's information need is further distributed among different representations based on weights***
- ***Object's similarity to query is calculated in terms of representations***

- *Representation's similarity is combined into feature's similarity*
- *By combing individual feature similarity overall similarity is calculated*
- *Objects are ordered by their overall similarity to query image*
- *According to user's perception user will marked retrieved images as highly relevant, non-relevant, no opinion, relevant*
- *System will adjust weights as per user's information need*
- *New iteration will start with updated weights.*

In earlier systems like Picture Archiving and Communications System which were using DICOM format for image storage, retrieval, transmission. Where as in web based systems images are stored and accessed in common formats JPEG and GIF. Md M Rahman et. al has given probabilistic multiclass SVM classifier and similarity fusion technique is based on two steps training and testing. In training feature vector set of images which are manually annotated with category label.In testing stage each non annotated image is classified against predefined categories. Each category will assign confidence to each image. Thus category label is assigned to respective image with highest score or confidence. As for different features number of classifiers have used to deal with problem of combining them combination rules based on Bayes theory that are namely sum, product, max, min, median are used. This results in final representation of feature vector of its confidence. After which similarity fusion in linear combination with certain weight is calculated this may be set manually or adjusted online.

In[6] statistical similarity matching function is used rather only comparing feature vectors of query and both supervised and unsupervised techniques are used by SVM classifier and FCM clustering respectively. This has also used prefiltering approach and Bhattacharya and Mahalanobis distance measures are used rather than Euclidean distance. It has proved their assumption that similarity measure and search functions outperforms when database is prefilterd rather when it is applied on whole database. The process proposed for similarity matching can be summarized as follows:

- *(Offline) During SVM training for predefined K classes calculate parameters mean and covariance*
- *For each query image and target images get category*
- *Utilize statistical similarity measure covariance matrix in Bhattacharya distance between query image and target image*
- *Convert distance measure and store array in descending order*
- *Finally return relevant images with similarity values*

In[13] image is represented at intermediate level to increase its accuracy. Its represented at concept level. An image contents number of concept as it is low level feature. Feature space is determined accurately by the correlations and structural relationships among the visual concepts.

In[9]precision at different rank position is calculated. It has given 30 - 40 % increase in mean average precision as compared to without using category information. In[10] as extension of previous work [6][9] Image filtering approach along with linear combination of similarity matching function with fix weight or weight updated by users feedback

Table 2 Review table

Sr.No.	Year	Author	Technique	Features of current techniques	Research gap
01	1999	C. R. Shyu et.al	CBIR ASSERT-System for HRCT images	Lung extraction algorithm, Efficiency measured by a speedup factor	Image retrieval for heterogeneous image database
02	2000	Thomas M.Lehman et.al	CBIR- A novel multistep approach, Feature transformation	Image comparison on the basis of prior knowledge of both query and image content	Satisfactory query completion
03	2000	Arnold W.M.Smeluders	CBIR(Review of CBIR at the end of early years)	Search by association, category search	Interpretation and similarity
04	2004	H Muller	CBIR	To replace text based retrieval but also complement with visual search tools	Visual features are used e.g. color,texture.Need to integrate functionalities in other existing application
05	2005	Thomas M.Lehmann et.al	Automatic categorization of medical images	Data mining	content based image retrieval that are no longer limited to special context are becoming possible
06	2007	MdMahmudur et.al	a novel image retrieval framework based on feature and similarity level fusions	Multiclass SVM and several classifier combination rules	Efficiency increases in terms of precision at each recall as difference in weighting scheme rather fixed weight.
07	2007	Md Mahmudur et.al	Image filtering by supervised and unsupervised technique. Statistical similarity matching,	SVM, FCM(Fuzzy c-mean)	Improved performance with use of covariance in similarity measure function
08	2008	W. Hsu et.al	SPRIS- Web-based distributed content-based image retrieval framework	Multiple partial shape matching and iterative querying	Improved retrieval quality by learning from user feedback; and improved user interaction and visualization.
09	2009	MdMahmudur et.al	Correlation Enhanced Visual Concept Feature Space	A spatial correlation-enhanced medical image representation and retrieval	feature space is enhanced by exploiting the correlations and structural relationships among the

				framework	visual concepts.
10	2010	MdMahmudur et.al	Classification driven image retrieval	Multiclass SVM and adjusts the feature weights in linear combination of similarity matching	Relevance feedback
11	July 2011	Md Mahmudur Rahman et.al	Biomedical image retrieval using SVM and relevance feedback	It gives10-15% improvement in precision at each recall value	RF Increases accuracy of retrieval

5. CONCLUSION

This review paper gives overview of Content Based Image Retrieval System. This work provides study of different approaches of CBIR and research gap.It is proved from previous work that performance of retrieval is better when search and similarity matching is performed on prefiltered dataset than whole database to reduce search space and searching at wrong place. We can conclude that for need of retrieving right image at right place and at right time we can built a efficient and effective framework with the use of different classifier with active relevance feedback. This analyzed work needs to be done in future for efficient Biomedical Image Retrieval

REFERENCES

1. C. R. Shyu, C. E. Brodley, A. C. Kak, A. Kosaka, A. M Aisen, and L. S. Broderick, "ASSERT: A physician-in-the-loop content-based image retrieval system for HRCT image databases," Comput. Vis. Image Understand., vol. 75, pp. 111–132, 1999.

2. T. M. Lehmann, B. B. Wein, J. Dahmen, J. Bredno, F. Vogelsang, and M. Kohnen, "Content-based image retrieval in medical applications-A novel multi-step approach," Proc. SPIE, vol. 3972, pp. 312–320, 2000.

3.
4. A.Smeulder, M. Worring, S. Santini, A. Gupta, and R. Jain, "Contentbased image retrieval at the end of the early years," IEEE Trans. Pattern Anal. Machine Intell., vol. 22, no. 12, pp. 1349–1380, Dec. 2000.

5. H. M¨uller, A. Rosset, J. Vallee, and A. Geissbuhler, "Integrating contentbased visual access methods into a medical case database," in Proc. Med Inf. Eur., St Malo, France, pp. 480–485.

6. T. M. Lehmann, M. O. G¨uld, T. Deselaers, D. Keysers, H. Schubert,K. Spitzer, H. Ney, and B. B.Wein, "Automatic categorization of medical images for content-based retrieval and data mining," Comput. Med. Imag.Graph., vol. 29, pp. 143–155, 2005.

7. M. M. Rahman, P. Bhattacharya, and B. C. Desai, "A framework for medical image retrieval using machine learning and statistical similarity matching techniques with relevance feedback," IEEE Trans. Inf. Tech.Biomed., vol. 11, no. 1, pp. 59–69, Jan. 2007.

8. W. Hsu, S. Antani, L. R. Long, L. Neve, and G. R. Thoma, "SPIRS: A web-based image retrieval system for large biomedical databases," Int. J. Med. Informat., vol. 78, pp. 13–24, 2008.

9. M. M. Rahman, S.K.Antani, andG.R. Thoma, "A medical image retrieval framework in correlation enhanced visual concept feature space," in *Proc.22nd IEEE Int. Symp. Comput.-BasedMed. Syst.*, Albuquerque, NM, Aug.3–4, 2009, pp. 1–4.

10. M. M. Rahman, S. K. Antani, and G. R. Thoma, "A classification-driven similarity matching framework for retrieval of biomedical images," presented at the 11th ACM Int. Conf. Multimedia Inf. Retrieval, National Constitution Center, Philadelphia, Pennsylvania, Mar. 29–31.

11. Md Mahmudur Rahman,Sameer K.Antani ang George R Thoma,"A Learning Based Similarity-Fusion and Filtering Approach for Biomedical Image Retrieval Using SVM Classification and Relevancs Feedback",IEEE Transaction on Information Technology in Biomedicine,VOL 15,NO 4,JULY 2011

12. X. S. Zhou and T. S. Huang, "Relevance feedback for image retrieval:A comprehensive review," Multimedia Syst., vol. 8, no. 6, pp. 536–544,2003.

13. Y. Rui and T. S. Huang, "Relevance feedback: A power tool for interactive content-based image retrieval," IEEE Circuits Syst. Video Technol., vol. 8,no. 5, pp. 644–655, Sep. 1999.

ISSN 2229-5518

14. M. M. Rahman, S.K.Antani, andG.R. Thoma “A medical image retrieval framework in corre-lation enhanced visual concept feature space”, inProc.22nd IEEE Int.Symp.Comput.BasedMed.Syst.,Albuquerque, NM, Aug.3-4, 2009, pp. 1-4.