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Effective RBIR Fuzzy C-Means Segmentation Haar Wavelet with User Interactive Multi Threshold Robust Features Vector

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Abstract: Region-Based Image Retrieval (RBIR) is proposed as a development of Content-Based Image Retrieval (CBIR). In this study, an RBIR system Fuzzy C-Means (FCM) algorithm is proposed for image segmentation, it automatically segments images into a variable number of regions and extracts each region as a set of features. In this study, a user interactive multi threshold scheme for Region based image retrieval is proposed. We use speeded up robust feature technique to extract the flat level features of the image. We excerpt the robust features of the image, each contains 124 values which helps to reduce the dimensionality. For each image there will be number of feature vectors, the extracted features will be indexed for further retrieval of images. At the query phase, the same set of features will be extracted from the query image and will be compared with the indexed feature vectors, here we accepted methodologies for facilitating semantic image analysis process. In addition, the system provide a feed back information that is used to elaborate the retrieval results and the overall procedure emerged until the user regards the returned results as satisfactory. This algorithm improves the performance of image segmentation and the time efficient final results will be returned according to the threshold specified. The user will be allowed to provide threshold in order to get the new set of results.

Key words: Region based Image retrieval, segmentation, speeded up robust features, multi threshold, fuzzy C-means

INTRODUCTION

Image retrieval has becoming an emerging technology and becoming the most popular research area now days. The increased form of digitally produced images requires new methods and techniques to access and retrieval. The popular image retrieval technique in Region based image retrieval where "RBIR" means is a promising extension of the classical CBIR, rather than employ global features over the entire content, RBIR systems partition an image into a number of homogenous regions and extract local features for each region. Here, the image retrieval framework has been introduced. This framework that combines efficient region based representation is used for storage and complexity and effective on-line learning potential (Jing *et al*., 2004). And, this framework contains the technique for region based image representation and contrast, indexing using modified inverted files, relevance feedback and learning region weighting (Stejic *et al*., 2003).

The region based image retrieval s used to searching a database of millions of images is a difficult task and lots of time constrained for that. Various features are used for indexing and retrieval of images. Shape, color and texture are most important features. These feature vectors have different type of images are stored and calculated as index of the images. Feature vector of the query image is calculated and compared with those index values for nearest image matching. The existing techniques cannot give the complete accuracy. So, this study, we improve the accuracy and performance. But, this approach was very sensitive and computation expensive.

That purpose we introduced a new standard approach is a global histogram is a plot of the number of pixels specified to each specific set of colors. The global histogram of query image and matching of database images drop bellow certain threshold, the images are examined to be similar. The crucial drawback of global histogram processing is it does not give any information about spatial distribution of colors. The existing image retrieval systems pays special awareness to the

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visualization of the image similarity criteria incorporated with the user's query image. This similarity criterion is either not explicitly constituted at all or is represented as a histogram showing the distribution of feature and/or region weights.

RBIR is a conventional technique which contains a set of approaches for retrieving semantic relevant images from image database, using low-level image features. This method was proposed for overcoming the limitations of text-based image retrieval by greatly appreciate the contents of image. For this, a similarity measure can be proposed for based on the integrated region matching measure. This method is to overcome the possible classification error. And, the feedback method is presented for the region based image retrieval. This method is enlarged to overcome the limitation of region based relevance feedback approaches (Papadopoulos *et al*., 2014). The feedback system provides the appropriate amount of information that is missing for managing a particular semantic image manipulation task.

RBIR generally indexes images by low-level visual features which, though they cannot completely distinguish semantic content, are easier to merge into numerical formulations. Nonetheless, retrieval performance of using low-level features alone is still far from satisfactory. To improve the performance is using region-based approaches to integrate local variations and spatial organization within images into the image matching criterion (Salembier and Marques, 1999). Finally, the Fuzzy C-Means (FCM) algorithm will be introduced for image segmentation. Image segmentation is one of the major key techniques in image understanding and computer vision. The function of image segmentation is to partitioning an image into a number of non overlapping regions, which have same attributes such as gray level, color, tone, texture, etc. A lot of clustering based methods has been proposed for image segmentation. Between the clustering methods, one of the most popular methods for image segmentation is fuzzy clustering, which can conserve more image information than strong clustering in some cases (Gong *et al*., 2013).

Fuzzy C-Means (FCM) algorithm is one of the most widely used fuzzy clustering algorithms in image segmentation. And, here the FCM_S is used to reduce the computational complexity. And, the computational time of EnFCM is very small. To overcome the above mentioned problems presents a novel robust Fuzzy Local Information C-Means clustering algorithm (FLICM) which is free of any parameter selection as well as promoting the image segmentation performance. The representation of features in image and similarity measurements of image are two important issues in content based image retrieval. In Region Based Image Retrieval (CBIR) process, the object of the query images are extracted and matches with each images of the database and provide result based on this their matching. In study, we compare the images by the multi threshold scheme and using the robust features. The features of the image are extracted from the query image are indexed and they are compared with the features of the image in the database. Where, the threshold value are allowed to given by the user. The results are provided based on the threshold value.

Back ground: Many of the researches were focused on developing the effective global visual features using region based image retrieval. Region-Based image Retrieval (RBIR) is used to overcome the drawback of global features by representing images at object-level, which are closer to the perception of human visual system. Here, the segmentation scheme was used. This scheme is called JSEG algorithm. Keeping that our determination is retrieval and the similarity measure that we use is inconsiderate to segmentation results, we combined the disconnected small region if they are close in space such that fewer regions are proceed for each image.

The existing image retrieval systems model the image similarity at the object level. The image similarity model must reproduce the region and feature saliency properties. The contribution of each region similarity to the overall image similarity should be weighted by the region importance. The fundamental objective of the image similarity model is to achieve image matching, and recognize the database images most similar to the user's query image. The region-based image similarity models express the image similarity as a collaboration of region similarities for classification. Image area is degrading into regions and each region is represented by a set of features, based on which region similarities are determined. The proposed similarity model is the extension of the Local Similarity Pattern (LSP) model.

And, the feature selection method is implemented for achieving the optimal balance between the requirements for selecting the greatest discriminative features and reducing the dimensionality. The proposed region-based RF procedure for improve the image retrieval results by taking into account the user's gaze signal is granted. This Feedback mechanism is used to maintain the low computational complexity. The relevance feedback

mechanism provides an interactive scheme to updates the matching criterion or the ideal query according to users' feedback (Li and Hsu, 2008). To estimate the region correspondence between all the feedback images in order to represent the ideal query in region level. The region and/or feature weights should also be updated accordingly. This study is to better approximate users' ideal queries using the region correspondence information estimated during image matching step.

Further, we introduced the FLICM for improve the performance. And, the objective function of FCM (KFCM) is used to replace the conventional measures. This method shows to be more robust and outlier in image segmentation. And also, we proposed two variants of KFCM which replace this term using the mean filtered (KFCM_S1) or median-filtered (KFCM_S2) image to reduce the computational cost. By introducing the fuzzy factor we improve the FLICM. And, KWFLICM removes almost all the added noise and maintains the image clear edge achieving satisfactory segmentation performance.

And, we discuss various existing techniques in retrieval of images according to the region of the images. Region based image retrieval based on high level features has been proposed by Latecki *et al*. (2000). High level features like pixel and color values been extracted and compared with other images to identify the similar images. The system only considers the colors of the image it does not worry or consider about the size of the image (Rui *et al*., 1999). To compute the relevancy, Euclidean distance is computed using which similar images are identified.

Region based image retrieval based on shape features are proposed by Belongie *et al*. (2002). Shape representations are normally divided into two types they are region based and boundary based. Earlier, the system uses the entire shape region later the system uses the outer boundary of the shape. Shape features present in the image is extracted and indexed. The retrieved feature vectors are indexed using hash based indexing scheme. At the retrieval face, the same shape features are identified and extracted and compared with the indexed feature vectors and the similarity values are calculated. Based on the calculated similarity values the results are returned. Region and concept based image retrieval is proposed in (Ling and Jacobs, 2007) visual features are extracted which represents the concept of the image and low level features like color, texture, Histogram of oriented Gradients (HoG), Local Binary Pattern (LBP), Harre are extracted and indexed for further retrieval of images. The RF method is examined for global-level feedback information in image retrieval. The asymmetric bagging and random subspace Support Vector Machine (SVM) efficiently handles the problems originate by the generally small number of positively labeled feedback samples.

MATERIALS AND METHODS

Proposed system: We propose a multi threshold scheme for content based image retrieval. Our system Fig. 1 supports user interaction so that the user can specify threshold according to which the results will be returned. The threshold value should be 0-1 and applied by the user instead of using Boolean operation (Ko and Byun, 2005). This process will be repeated up to the user gets satisfied. Our algorithm works as follows, first the interest points are identified using the hessian matrix equation in the image which user applied threshold value and the feature descriptors are generated using the haar wavelets matrix for the selected image and the generated feature descriptors are indexed. Later feature descriptors are generated from the source image and compared with each of the feature descriptors indexed into the system.

Another scheme for Segmentation aims at creating a partition (that is, a specific region-based representation) of the original data. Many algorithms try to progressively convert the pixel-based representation into an initial region-based representation and then act on this region based representation to obtain the final partition by splitting or merging steps.

And, we propose a new method is called RBIR. In the RBIR method, automatically segments images into a variable number of regions and extracts for each region a set of features. Although, relevance feedback has exhibited its significant possible in improving the retrieval performance in RBIR systems that use global features representations (Jing *et al*., 2004). And, the feedback mechanism has been proposed for to maintain low computational complexity. This method aims to learn the ideal data graph and simultaneously refine the image distance measurement based on the feedback model graphs. We assume the ideal data graph has similar spatial organization with the initial data graph and thus include the estimated matching matrices between the initial data graph and the feedback model graphs into the formulation. Finally, improves the performance of image segmentation.

Region based image retrieval: In the proposed region based image retrieval, images in the database are first segmented into homogeneous regions. The image similarity measure is defined based on the Earth Mover's Distance. To be efficient, a novel indexing scheme is

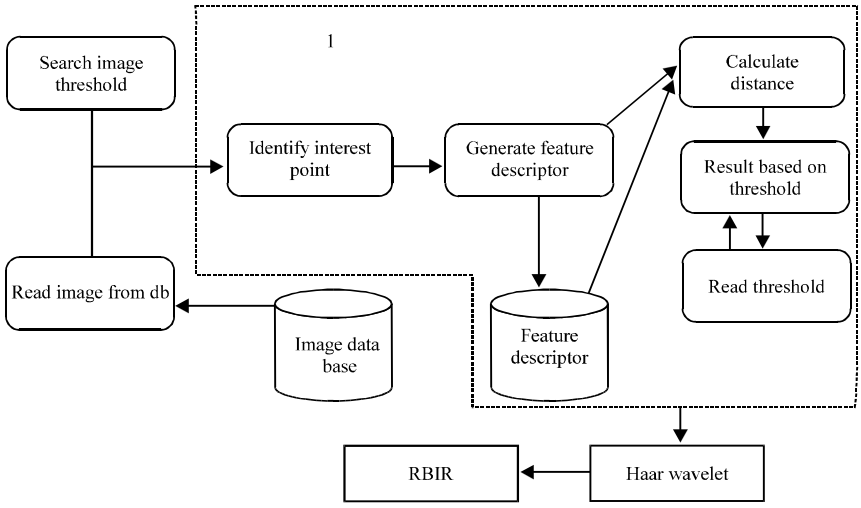

Fig. 1: Block diagram for RBIR fuzzy C-means segmentation Haar wavelet with user interactive multi threshold robust features vector

Fig. 2: a) Original image and b) Segmented result

proposed to quickly filter out candidate images before the similarity between the query and an image in the database is calculated. EMD incorporates the properties of all the segmented regions, so that information about an image can be fully utilized. EMD is based on the transportation problem and can be solved efficiently by linear optimization algorithms that take advantage of its special 2structure: EMD incorporates the properties of all the segmented regions so that information about an image can be fully utilized. By allowing many-to-many relationship of the regions to be valid, EMD is robust to inaccurate segmentation.

Segmentation: Segmentation techniques often use more than one feature. This can be done either through the definition of a complex criterion combining several features or through the use of several segmentation steps that use different criteria. In this study, we analyze the main segmentation approaches for multimedia services from the viewpoint of the type of decision they use. A region created by a segmentation algorithm is defined as a set of elements (pixels or images) homogeneous in the feature space and connected in the decision space. A region may not have any semantically meaning (Fig. 2).

Interestpoint identification: Normally, the image contains large amount of data which are difficult to analyze. Not all the data are important for the retrieval. To reduce the complexity of the image data we use interest point identification (Chavez, 2008). A "point" normally refers to the image region with centered specific point Interest point provides perfect representation of image contents. Image convolutions with these box filters can be computed rapidly by using integral images. Box filter are the spatial averaging filter in which all coefficient are equal. Once (Zilly *et al*., 2011) we have computed the integral image, it is strait forward to calculate the sum of the intensities of pixels over any upright rectangular area (Fig. 3):

$$D\left(I_{p,}\, I_{q}\right)=\sum_{i=1}^{m}\sum_{j=1}^{n}{}_{ij}\, d\left(CI_{pi},CI_{qj}\right)$$

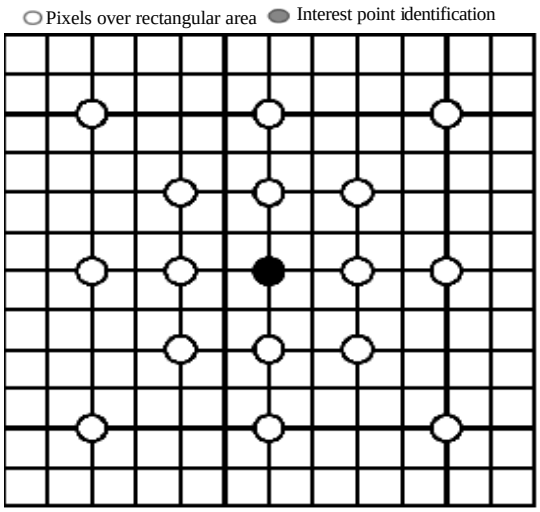

Fig. 3: Iterest point identification in an image

Fig. 4: Sub region formation of an image

The location and scale of interest points are selected by relying on the determinant of the Hessian. It determines the location and scale of the descriptor:

$$H(x,\sigma)=\begin{bmatrix} L_{xx}(x,\sigma)L_{xy}(x,\sigma) \\ L_{xy}(x,\sigma)L_{yy}(x,\sigma) \end{bmatrix}$$

where, Lxx (x,σ) is a Gaussian second order derivative and similarly for $L_{xy}(x,\sigma)$ and $L_{yy}(x,\sigma)$. The determinant of the Hessian matrix written as:

$$Det\left(H_{apprpx}\right)=D_{xx}\ D_{yy}-\left(0.9D_{xy}\right)^2$$

SURF constructs a circular region around the detected interest points in order to assign a unique orientation to the former and thus, gain invariance to image rotations. The orientation is computed using Haar wavelet responses in both x and y direction.

Feature descriptors generator: Feature descriptors characterize the region in the robust way which is invariant to natural viewing changes. It includes rotation, lighting, scale and view point variance Rui *et al*., 1999). The SURF descriptors are constructed by extracting square regions around the interest points. These are oriented in the directions assigned in the previous step. The windows are split up in 4 by 4 sub-regions in order to retain some spatial information (Fig. 4).

In each sub-region, (Talukder and Harada, 2010) Haar wavelets are extracted at regularly spaced sample points. In order to increase robustness to geometric deformations and localization errors, the responses of the Haar wavelets are weighted with a Gaussian, centered at the interest point. Sample haar function t = m/N; where m = 0, 1, 2, 3,…, N–1. To form an N by N matrix for discrete Haar transforms. For example, when N = 4 we have:

$$H4=1/2\begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & -1 & -1 \\ \sqrt{2} & \sqrt{-2} & 0 & 0 \\ 0 & 0 & \sqrt{2} & \sqrt{-2} \end{bmatrix}$$

When N = 8:

$$H_8=\frac{1}{\sqrt{8}}\begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & -1 & -1 & -1 & -1 \\ \sqrt{2} & \sqrt{2} & -\sqrt{2} & -\sqrt{2} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sqrt{2} & \sqrt{2} & -\sqrt{2} & -\sqrt{2} \\ 2 & -2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & -2 & 2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 2 & -2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 2 & -2 \end{bmatrix}\begin{matrix} \varphi_0(t) \\ \varphi_0(t) \\ \varphi_{1,0}(t) \\ \varphi_{1,1}(t) \\ \varphi_{2,0}(t) \\ \varphi_{2,1}(t) \\ \varphi_{2,2}(t) \\ \varphi_{2,3}(t) \end{matrix}$$

Finally, the wavelet responses in horizontal xd and vertical directions yd are summed up over each sub region. Furthermore, the absolute values are summed in order to obtain information about the polarity of the image intensity changes. Hence, the underlying intensity pattern of each sub-region is described by a vector. C-means algorithm in segmentation is done with image pixel and

neighboring pixel feedback value and high feature vector is used to have effective retrieval of region.

Feedback mechanism: Normally, the feedback mechanism is used for updating the image retrieval results, by taking into account the user's gaze signal, is presented in this study. The RF mechanism is formalized as follows: The composite image at iteration r, denoted as CI(t), comprises all image regions that have been seen by the user from the beginning of the session, along with their corresponding degree of relevance rd ($s^{m}/_{n}$) and is represented according to the following equation:

$$CI(t)=\left\{\left(S_{ny}^{my},rd\left(S_{ny}^{my}\right)\right),y\in[1,r]\right.$$

In this study, our feedback technique adopts the estimated region correspondence, the irrelevant feedback regions will be automatically eliminated in the feedback process.

Feature descriptor matching: The feature descriptors from the query image are extracted and indexed. The indexed features are compared with the features of the images which are present in the database. The algorithm of image features extraction involves decomposition, the Haar transform of each sub image Ii, j of size 4×4 taken from the image

Key points match is done between two images typically. Given a pair of images Ii, Ij with their respective interest points and feature descriptors for every interest point in the first image Ii, we calculate the Euclidian distance to all feature descriptors in the second image Ii:

$$\text{Formula edu dis}=\text{sqrt}\left(\left((\text{row1}-\text{row2})+\right.\right.$$
$$\left.\left((\text{Col1}-\text{col2}).\wedge 2\right)\right)$$

If the ratio of the nearest neighbor and the second-nearest neighbor (Sharvit *et al*., 1998) is smaller than a predefined threshold which is discussed in the experiment, a match is assumed to be correct and is therefore added to the list of putative matches. In our study, the match process of key points is done by matching between two subsets of the key points set of the test image. The distance between feature descriptor is calculated and similar images are identified if the distance is less than the threshold specified by the user. This will be repeatedly carried out up to the user gets satisfied Fig. 5.

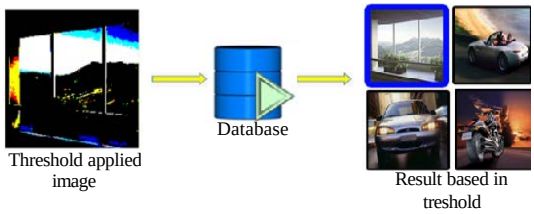

Fig. 5: Model output for feedback feature vector segmented C-means algorithm

RESULTS AND DISCUSSION

From obtained results, classification accuracy for different combinations of values for parameters and obtained using the feature vector technique are illustrated in below Fig. 6. From the obtained results, it can be seen that the maximum performance is obtain for most values of parameter, while significantly low or high values of lead to decrease in performance. Additionally, it is shown that when selecting 124 features from a pool of 450 available temporal- and spatial-related ones when leads to the best overall performance. Similar behavior, achieving a maximum classification performance for and around a particular value of, was also observed for the other feature selection techniques.

- Feature Vector (FV): a feature vector is an n-dimensional vector of numerical features that represent some object

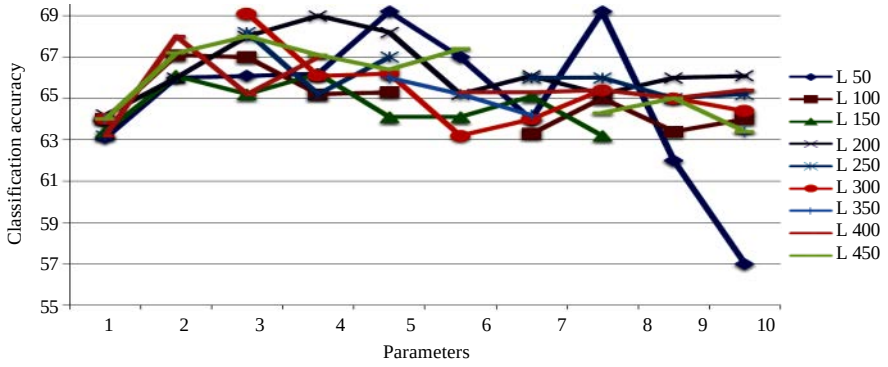

Fig. 6: Classification accuracy with Z vs. L function value

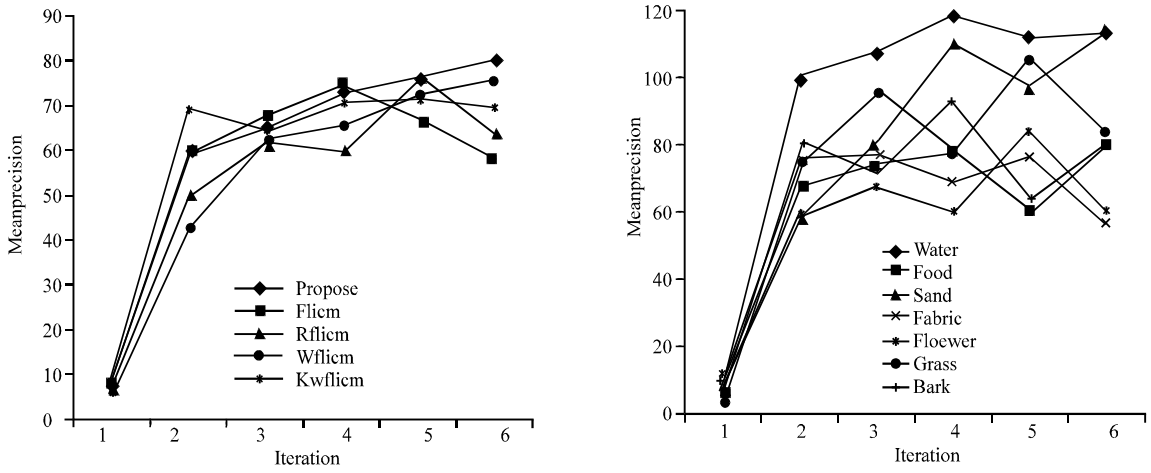

Fig. 7: Proposed [FBVSCM] overall analysis and individual image group analysis

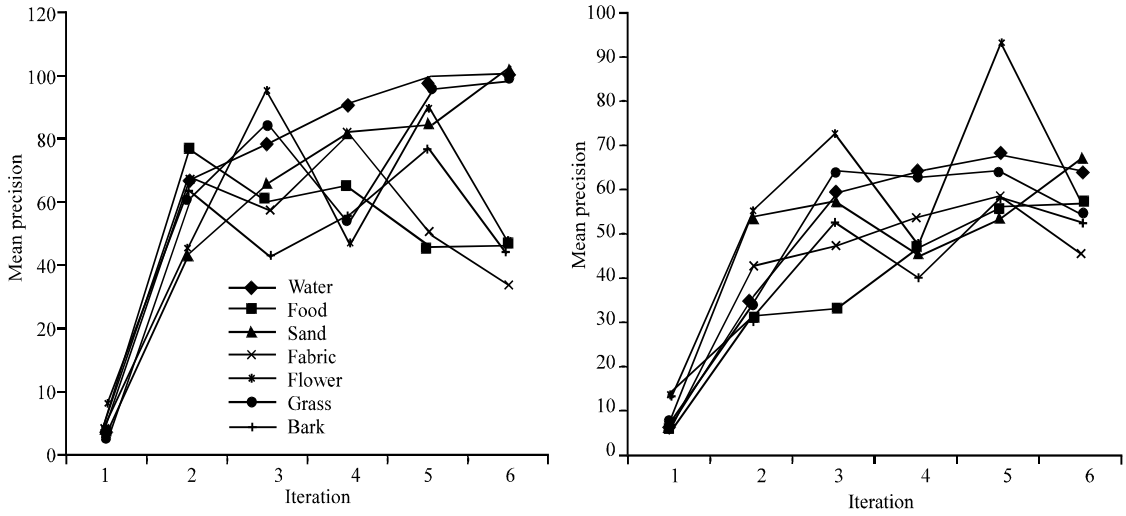

Fig. 8: WFLICM and KWFLICM individual image group analysis

- FLICM: FLICM (Robust Fuzzy Local Information C-Means clustering algorithm) is used for fuzzy local (both spatial and gray level) similarity measure, pointing to covenent noise insensitiveness and image detail conservation. Also, FLICM can overcome the disadvantages of the C-Means algorithms and enhances the clustering performance
- RFLICM (replace): This scheme allows the segmentation of tumor tissue with accuracy comparable to other method
- WFLICM (weighted) can overcome the disadvantages of the known fuzzy C-means algorithm and at the same time, enhances the clustering performance
- KWFLICM (kernal): reduces the memory usage which increses some level of performance
- FBVSCM (feedback feature vector segmented C-means algorithum): Compare to other methods this method is effective it will give more performance

Figure 9 initial query applied for retrival it produces some effective result. When applying initial first feedback the retrival ratio incresed, when second feedback applied the precision value incresed when applying further feedback the effective result is obtained. When considering theefficiency it produce effective result in reduced time.

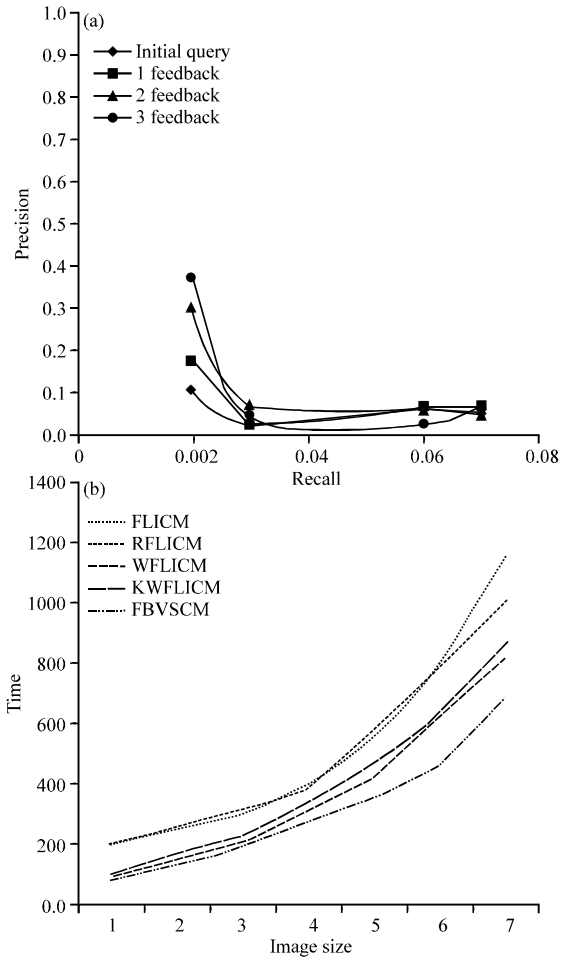

Fig. 9: RBIR level of FBVSCM and time efficiency analysis of FBVSCM

CONCLUSION

The main contribution of this is implementing a RBIR method, this method automatically segments images into a variable number of regions and extracts for each region a set of features vector and analyzed high value vector. In this study, we propose a FCM algorithm for segmentation of images. Segmentation is used to partitioning the image into a number of non overlapping regions and this study also introduces an effective to constructing a resilient image clustering algorithm.

Finally, the feedback mechanism is implemented for improving the image retrieval results and this feedback mechanism is used to reduce the computational complexity and improves the performance of image segmentation.

There by RBIR has performed with effective retrieval by feature vector, Haars wavelet relevance feedback and fuzzy C-means with reduced time and good performance.

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