Investigation of Modified Fuzzy C-Means Clustering with Content based Retrieval Image Technique for Medical Diagnosis

L. Malliga and K. Bommanaraja

Department of ECE, SSM Institute of Engineering and Technology, Dindigul, India
Department of BME, PSNA College of Engineering and Technology, Dindigul, India

Abstract: In medical images, Content-based image retrieval (CBIR) is a primary technique for computer-aided diagnosis. Many research works were developed in content based medical image retrieval, but the techniques have the drawback of low efficiency and high computation cost. To avoid such negative aspects a new enhanced Content Based Medical Image Retrieval (CBMIR) based on MFCM clustering technique is proposed in this paper. To retrieve the images, initially the features are extracted from the database medical images by using Haar. Thus the extracted features from the training database images are clustered by the FCM clustering technique. After in the retrieval process, the training image database feature values are differenced with the training images clustered result values. Based on the distance values, the most relevant images are retrieved. Hence, our proposed technique will efficiently retrieve the most relevant medial images via MFCM technique with retrieval rate.

Key words: Content Based Image Retrieval (CBIR) • CBMIR • Discrete Wavelet Transform (DWT) • Fuzzy C-Means (FCM) • Clustering

INTRODUCTION

In recent years, an efficient method of image searching and retrieval has increased. It can simplify many tasks in many application areas such as biomedicine, forensics, artificial intelligence, military, education, web image searching. Image retrieval is the process of browsing, searching and retrieving images from a large database of digital images [1]. Generally, three categories of methods for image retrieval are used: text-based, content-based and semantic-based. Content Based Image Retrieval (CBIR) is a prominent area in image processing due to its diverse applications in internet, multimedia, medical image archives and crime prevention [2]. Some of the popular CBIR systems developed in the academia and the industry are QBIC, Ne TRA, MARS, Blob world, PicToSeek and Simplicity besides others

CBIR is the process of retrieving images from a database or library of digital images according to the visual content of the images. It overcomes the difficulties of manual annotations by using visual feature based representations, such as color, texture, shape, etc. It aims at reducing the need for textual description and to provide the most appropriate images automatically and computationally faster. Many different approaches for content-based image retrieval have been proposed [7]. CBIR for medical images has become a major necessity with the growing technological advancements. Medical images are usually fused, subject to high inconsistency and composed of different minor structures. So there is a necessity for feature extraction and classification of images for easy retrieval [12]. computed tomography scanners (CT), magnetic resonance imagers (MRI), ultrasound probes (US) and nuclear imagers are the most widely used.

They provide images in terms of resolution, contrast and signal to noise ratio. CBIR has the possibility to give medical doctors with accurate result in diagnoses[10]. For example, CBIR system is used to diagnosis a patient result based on the existing patient disease details.

Some of the CBIR medical applications are Cancer Detection, Bone Age Estimation [17]. The rest of the paper is organized as follows, The proposed content based medical image retrieval (CBMIR) process is briefly...
explained in section 2. Our proposed technique experimental results and the conclusion of the paper are given in section 3 and 4.

Proposed Content Based Medical Image Retrieval (CBMIR) Technique: Our proposed content based medical images retrieval (CBMIR) technique retrieves the more relevant query images by using the Modified FCM (MFCM) algorithm. Based on the the given input query images, relevant images are extracted from the database. The proposed CBMIR technique mainly comprised of three stages namely (i) Feature Extraction (ii) Features clustering and (iii) Image retrieval. The three stages of proposed CBMIR technique are discussed in section 2.1, 2.2 and 2.3 respectively.

Structure of our proposed CBMIR technique is illustrated in Fig. 1 initially the database medical images are given to the first stage to extract the features. In feature extraction, a Haar wavelet transform is utilized to extract the wavelet features from the database images. Thus the extracted features from the database images are stored in the feature database which is utilized in the clustering process. In second stage, the extracted features are clustered by using the MFCM clustering algorithm. In clustering, the similar images equivalent features are grouped in one cluster and their centroid values are also stored.

In image retrieval stage, the query images features are also extracted by using the Haar wavelet technique. Afterward, to retrieves the images that are equivalent to the query image, we compute the distance between the feature values which are extracted from the query images and the clusters centroid values. The most relevant images are retrieved from the clusters which have the small distance value. The brief discussion of the three stages in CBMIR technique is explained in the following sections.

Feature Extraction: In feature extraction the given database image wavelet features are extracted and by utilizing these extracted features feature vectors are constructed which are exploited in the image retrieval process. In our proposed technique, a Haar wavelet transform is utilized in the feature extraction process. Before the feature extraction an input image is to be preprocessed by resizing the database images. In order to normalize the data and not to have any differences related to sizes of the images, we first rescale the images to 128x128 pixels. There are 3 interpolation techniques built in Mat lab for resizing images: nearest-neighbor interpolation, bilinear interpolation and bicubic interpolation. But in our technique a bicubic interpolation technique is utilized because it is most accurate among the methods. After the image resizing process, the resized images are decomposed by the Haar wavelet transform.

Thus the resized result image from the bicubic interpolation technique is denoted as . I,

Haar Wavelet Transform: Currently, it has been proved that the Wavelet Transform is a very precious tool for image processing. By means of wavelets, a function can be depicted in terms of a coarse overall shape, plus details that range from broad to narrow. The most unique feature of Haar Transform (HT) is that it allows simple manual calculations. The wavelet transform is normally employed for signal and /or image smoothing by considering its “energy compaction” properties, i.e., large values are likely to become larger and small values smaller, when the wavelet transform is applied.

The Haar Transform is swift, simple and memory efficient and also it is exactly reversible without the edge effects. Thus, the Haar Transform method is extensively used for wavelet analysis in recent days. We apply Haar wavelet transformation is to divide the image into its high and low frequency bands and construct feature vectors from the low-pass filtered image components. After the Haar wavelet transformation is completed, the original matrix is divided into four sections, where the upper left part of the image passed through horizontal and vertical low filters. We know that low frequency bands represent the gross features of the image which we are interested in. Haar wavelet transformation can be applied several times. When we say 4-level wavelet transformation, this means we apply transformation iteratively 4 times.

The 4-level Haar wavelet transformation process on the image is represented as Fig. 2. In our approach, we apply 4-level Haar wavelet transformation to the image. We store the upper left 16x16 matrixes, which are also divided into its high and low frequency components, as part of the feature vector.

Finally, we apply 1 more level transformation to each component and store these 8x8 matrixes and their standard deviations as part of the feature vector. For an each input image, we are storing an 8x8 and 16x16 matrixes and the standard deviation of the 8x8 matrix. Thus the obtained feature vector from the wavelet transformation is denoted as.

Fig. 1: Structure of our proposed CBMIR Technique

Fig. 2: Image partition after 4-level Haar wavelet transformation

\[ w(I) = \{m_1, m_2, \sigma\} \] (1)

In Equ. (1) and is the 16x16 and 8x8 matrix values and represents the standard deviation value of the matrix \( m_2 \). The standard deviation is calculated by,

\[ \sigma = \sqrt{\frac{1}{A-1 \times B-1} \sum_{a=1}^{A} \sum_{b=1}^{B} (p_{ab} - \mu(m2))^2} \] (2)

In Equ. (2), \( p_{ab} \) is the pixel value of the matrix with the size of \( a \times b \).

To improve the more accuracy in the image retrieval process other image features like Mean, Variance, entropy, energy, contrast and homogeneity are extracted from the database images. These features are computed by,

\[ \mu(I_i) = \frac{1}{M \times N} \sum_{m=1}^{M} \sum_{n=1}^{N} p_{mn} \] \hspace{1cm} (3)

\[ V(I_i) = \frac{1}{M \times N} \left( \sum_{m=1}^{M} \sum_{n=1}^{N} (p_{mn} - \mu(I_i))^2 \right) \] \hspace{1cm} (4)

\[ E(I_i) = \sum_{m=1}^{M} \sum_{n=1}^{N} (p_{mn})^2 \] \hspace{1cm} (5)

\[ En(I_i) = -\sum_{m=1}^{M} \sum_{n=1}^{N} p_{mn} \log p_{mn} \] \hspace{1cm} (6)

\[ C(I_i) = \sum_{m=1}^{M} \sum_{n=1}^{N} (m-n)^2 p_{mn} \] \hspace{1cm} (7)

\[ H(I_i) = \sum_{m=1}^{M} \sum_{n=1}^{N} \frac{p_{mn}}{1 + |(m-n)|} \] \hspace{1cm} (8)

In Equ. (3) to (8) denotes the computed image features like Mean, Variance, Entropy, Energy, Contrast and Homogeneity of the image and the image size is
defined as $M \times N; 0 \leq m \leq M, 0 \leq n \leq N$. In additional there are two features like no of regions and object shape features are also extracted from the input images.

**Features Clustering:** Thus the extracted features from the feature extraction process are clustered by the modified FCM technique. The extracted image features are grouped in one cluster which has the similar values. The features clustering process by MFCM technique objective function is given by,

$$O = \sum_{k=1}^{K} \sum_{r=1}^{R} (1 - \beta) m_k^r \left| f_k - c_r \right|^2$$  \hspace{1cm} (9)

The MFCM objective function is modified by multiplying the constant value $\beta$ with the membership function. In Equ. (9), $m_k$ is the degree of membership of $f_k$ in the cluster, $f_k$ is the data and $c_r$ is the centroid value of the cluster $r$, || is the similarity between any measured data and the cluster center. The data is partitioned by the fuzzy function and the membership and cluster center are updated by,

$$m_k = \frac{1}{\sum_{s=1}^{R} \left( \frac{||f_k - c_s||}{||f_k - c_r||} \right)^{m-1}}$$  \hspace{1cm} (10)

Thus the extracted features from the feature extraction process are clustered by the modified FCM technique. The extracted image features are grouped in one cluster which has the similar values. The features clustering process by MFCM technique objective function is given by,

$$O = \sum_{k=1}^{K} \sum_{r=1}^{R} (1 - \beta) m_k^r \left| f_k - c_r \right|^2$$  \hspace{1cm} (11)

The MFCM objective function is modified by multiplying the constant value $\beta$ with the membership function. In Equ. (11), $m_k$ is the degree of membership of $f_k$ in the cluster $r$, $f_k$ is the data and $c_r$ is the centroid value of the cluster $r$, || is the similarity between any measured data and the cluster center. The data is partitioned by the fuzzy function and the membership and cluster center are updated by,

$$m_k = \frac{1}{\sum_{s=1}^{R} \left( \frac{||f_k - c_s||}{||f_k - c_r||} \right)^{m-1}}$$  \hspace{1cm} (12)

The process is repeated when the iteration is reached. The centroid values from the MFCM clustering are denoted as $C = \{c_1, c_2, ..., c_R\}$ where $R$ is the number of clusters. In FCM algorithm [31] each pixel of an image can have membership to more than one cluster which is not in case of K-means algorithm. The modified FCM [32] has many advantages like than the existing FCM [30], as because MFCM,

- Eliminates noisy spots Reduces false blobs
- Less sensitive to noise More homogeneous regions are obtained

**Image Retrieval:** In image retrieval, the query images equivalent most relevant images are extracted from the training database by using the distance measure. The distance measure is computed by using the query image feature values and the training database images clustered centroid values. The process of query matching by the distance measure is described below.

**Query Matching:** The query image $q$ feature vectors are represented as $f_q = \{f_{q1}, f_{q2}, ..., f_{qL}\}$ which is obtained from the feature extraction process. Similarly, each image in the database is represented with the feature vector $f_d = \{f_{d1}, f_{d2}, ..., f_{dL}\}, i=1,2,...,|D|$ and their cluster centroid values is $C_{centroid} = \{c_1, c_2, ..., c_R\}$. Our main objective is to select top matched images by measuring the distance between the query and the images in the database $D$. In order to retrieve the images a Euclidean distance measure is computed by,

$$QM(f_q, C_{centroid}) = \min_{r=1,2,...,R} \left( \frac{1}{L} \sum_{l=1}^{L} (c_{rl} - f_{ql}) \right)$$  \hspace{1cm} (14)

where $L$ denotes the length of the feature and centroid values. By exploiting the Equ. (14), the relevant images are extracted which have the minimum value of $QM$. In Equ. (14), the query image feature vectors values are distinction with the cluster centroid values and retrieve the images from the cluster which have the small distance. Our proposed content based medical image retrieval (CBMIR) process as explained by the algorithm, which is given below.
RESULTS AND DISCUSSION

The performance of the proposed CBMIR technique is evaluated by different type and number of medical images namely, MRI brain images, lung images, liver images, mammogram breast images and ultrasound kidney stone images. Those set of medical images are used in the medical images retrieval performance analysis process. The sample medical images of each type are given in Fig. 3.

The wavelet features are extracted from the database medical images and the extracted features are clustered by the MFCM clustering. To analyze our proposed technique performance, the sample query image is given to retrieve the most relevant images from the database. For the retrieval process the Haralick and texture spectrum features are also computed for the given query images and find the difference between these query image features and the clustered features centroid values. Based on the difference the images are retrieved from the database. If the retrieved image is belongs to the category of the query image means that our proposed technique properly find the expected image, or else the technique has failed to find the probable image. The sample query images from the database are given in Fig. 3.

The retrieved image results for the corresponding query images are given in Fig. (4), are illustrated in Fig. 4.

Performance Analysis: Our proposed CBMIR technique performance is evaluated by two quantitative performance metrics are given below,

- Average Retrieval Rate (ARR)

\[
ARR = \frac{1}{N_q} \sum_{q=1}^{N_q} RR(q) \leq 1
\] (15)

The first quantitative evaluation metric is Average Retrieval Rate (ARR) is given in Equ. (15) In Equ. (23), \(N_q\) represents the number of queries that are used for verifying the retrieval performance and RR, represented the retrieval rate of a single query image. The RR can be computed by the following Equation,

\[
RR(q) = \frac{N_{r,q}(q)}{N_{dr,q}(q)} \leq 1
\] (16)

In Equ. (16), \(N_{r,q}(q)\) denotes the number of relevant images in the database D of the query q and \(N_{r,q}(q)\), denotes the number of retrieved relevant images of the query q. The high ARR value indicates the good performance of image retrieval whereas low value indicates a bad retrieval rate.

- Average Precision Rate (APR)
Moreover the other metrics namely, precision and recall are utilized in the different feature extraction methods performance evaluation in retrieving the most relevant images from the given database. The different feature extraction methods performance results in terms of precision and recall measures are illustrated in Fig. 5.

The precision and recall values are calculated by using the following equations,

\[ p = \frac{N_{rr}}{N_r} \]  

\[ R_{recall} = \frac{N_{rr}}{N_d} \]  

Retrieval Performance: Our proposed CBMIR retrieval performance is evaluated with more number of medical images by using the aforementioned performance metrics such as ARR and APR. Moreover, our proposed feature extraction technique performance is compared with other feature extraction methods like PCA, Gabor filter and retrieval technique using K-means clustering. The image retrieval results by our proposed MFCM based retrieval and K-means based retrieval is given in Fig. 4.
Fig. 4: Retrieved Images for (i) Query image 1 (ii) Query image 2 and (iii) Query image 3
Fig. 4: Retrieval Performance of proposed CBMIR with MFCM based retrieval and K-Means based retrieval
In Equ. (19), \( N_r \) denotes the number of relevant images retrieved, \( N \) represents the total of retrieved images and \( N_j \) is the total number of images in the database.

In Fig. 5, the different feature extraction methods retrieval results are analyzed in terms of their precision and recall rates. The graph results shows that our proposed feature extraction technique has given high precision and recall rates than the other feature extraction methods. It shows that in our proposed method the usage of the haar wavelet feature extraction methods has given high retrieval rate, which is shown in below table.

The Quantitative performance metrics results for different feature extraction methods with MFCM and K-Means retrieval results are given in Table 1.

As can be seen from Table 1, the high value of ARR and APR shows that our proposed feature extraction technique with MFCM based retrieval techniques has given the good retrieval rates than the other K-means based retrieval techniques. Our proposed method has given 83% and 65% value of the ARR and APR values. The results value from our proposed method shows that our proposed method retrieves more relevant images for the query image.

CONCLUSION

In this paper, we proposed an enhanced CBMIR technique which retrieves the relevant medical images from the given image database for a given query image. Initially, the wavelet features are extracted from the given query and database images. By exploiting these extracted features the similar images are clustered by the MFCM
technique. Next, the distinction value is computed between the query image features and clustered centroid values, based on these distinction value the most relevant images are retrieved. The performance of the proposed system was evaluated by the more number of query images. The implementation results shows that the proposed CBMIR technique efficiently retrieves the most relevant medical images from the image database than the other CBIR methods. The results show that our proposed CBMIR attains more precision and recall results in retrieves the most relevant images from the medical image database.

REFERENCES


