**I J C T A**, 9(28) 2016, pp. 133-140


# AN INTEGRATED APPROACH FOR CONTENT BASED IMAGE RETRIEVAL SYSTEM USING WAVELETANDFUZZYC-MEANSALGORITHM

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***Abstract:*** Content Based Image retrieval (CBIR) using wavelet and fuzzy c-means algorithm through Euclidean Distance similarity measure is proposed in this framework. In this proposed approach wavelet decomposes an image into four subbands and the features such as energy and standard deviation are extracted from wavelet subbands. Then the wavelet based features are clustered by using fuzzy C-means algorithm.The most similar classifications are found from the database images as in the query by using Euclidean distance measure. Euclidean distance (ED) is suitable and more effective method over other distance measurement. This proposed approach gives better classification rate when compared to the existing methods.

***Keywords :*** Medical Image retrieval, EEWT, Euclidean Distance, DWT.

## 1. INTRODUCTION

CBIR is a set of process for retrieving appropriate images from an image database based on automatically-derived image features. The main objective of CBIR is image indexing and retrieval, thereupon reducing the indispensability of human interference in the method of indexing. CBIR features are extracted for classification from the database and query images based on its statistical values, namely energy and standard deviation (Manesh Kokare et al 2005). These features become the image of perceptive illustration for computing the measure of similarity. An image is compared to other images by computing the difference between their corresponding features. In this paper, integrated approach for wavelet and Fuzzy c-means has been proposed. In CBIR, texture features play a very significant task in computer vision and pattern recognition, mainly in relation to the content of images (Hsin-Chih Lin 1999). We make use of Fuzzy C- means algorithm for assigning multiclass membership values to each pixel, for approximate segmentation into homogeneous regions. Importance of the texture feature is due to its occurrence in lots of real world images for example clothes, clouds, trees, and bricks. All of which contain textural individuality. Earlier methods for texture image retrieval had suffered features from two major drawbacks (Manjunath & Ma 1996) (Do & Vetterli 2002). They are either computationally expensive or retrieval accuracy is poor. In this paper, we proposed a simple technique to identify uniform textured regions. The approximate boundary regions are also extracted for detecting the differences of textures in adjacent regions. The performance is compared with other approaches like DWT and RCWF with CD and DT-CWF with PCA to prove the efficiency of the proposed approach. The remaining sections are organized as follows. The CBIR is described in section 2.Section 3 shows the proposed approach. Fuzzy c-means algorithm described in section 4. The Euclidean Distance and Experimental results are made in section 5 and section6.

## 2. CONTENT BASED IMAGE RETRIEVAL

Content-based image retrieval systems have been dealt with the issue of automatic indexing and retrieval of images [4]. The general image retrieval system is shown in Figure 1. It consists of three main modules such as database module, query module, and retrieval module.

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In the database module, the feature vector is extracted from database images. It is then stored along with its database image. On the other hand, when a query image enters the query module, it extracts the feature vector of the query image. In the retrieval module, the extracted feature vector is compared to the feature vectors stored in the image database. As a result of query, the similar images are retrieved according to their closest matching scores. Finally, the target image will be obtained from the retrieved images.

## 3. CBIR USING WAVELET AND FUZZY CLUSTERING THROUGH ED MEASURE

In our proposed CBIR system, an image of both query and database are normalized and resized from the original. Consequently, each of which are associated with a feature vector derived directly from discrete wavelet transform. Extracted features are clustered by using Fuzzy C-Means clustering. The retrieval is the relevance between a query image and any database image as shown in Figure 2, the relevance similarity is ranked according to closest similar measures computed by the Euclidean distance [5].

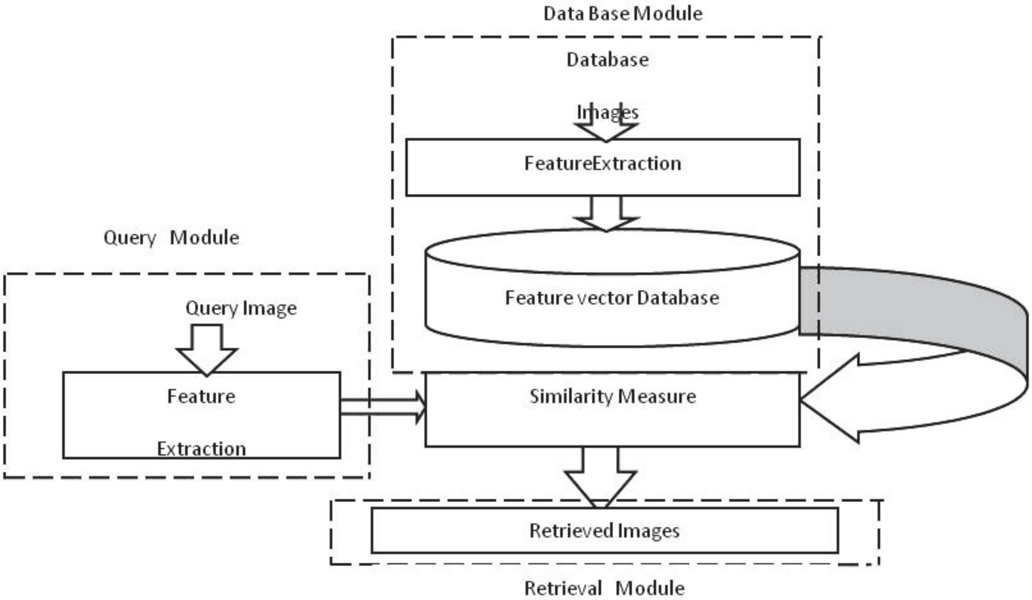


**Figure 1. Block Diagram**

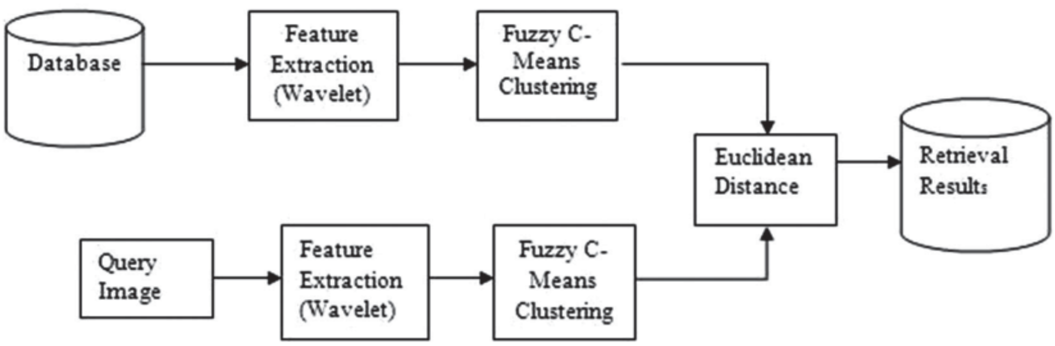


**Figure 2. Proposed method**

As a result, the similar images are retrieved according to their closest matching scores. Finally, the most relevant images are to be obtained from the retrieved images. Similar images are identified by using ED measurement. This ED measure provides better result than other distance measure.

## 2.1 Wavelet Transforms and Multiresolution Analysis

The history of the wavelet transforms traces back to Fourier transform. In Fourier decomposition, a signal is prolonged as an important of sinusoidal oscillations more than a range of frequencies. This result in an orthonormal, linear and invertible transforms which has been preferably applied to different areas in engineering. Anyhow, the main drawback of Fourier theory is its poor time-frequency characteristics. The requirement of any time information in a Fourier expression makes this system unsuitable for a lot of actual world signals. Therefore joint time-frequency illustrations were born. A regular component surrounded by these representations is some mechanism that allows a trade-off between time and frequency resolutions. The first of such illustrations is the Windowed Fourier Transform, which employs an added time window in the transform. In particular, the Gabor transform is one such transform with a Gaussian window (Ahmadian & Mostafa 2003). Time-frequency representations later developed to other forms which do not use windowed sinusoids as the analytical basis.

## 2.2 Feature Extraction Through Wavelet

There are a number of basis functions that can be utilized as the mother wavelet for wavelet Transformation. Although the mother wavelet make all wavelet functions applied in the transformation through translation and scaling it decides the characteristics of the ensuing wavelet transform. Then, the facts of the particular application should be taken into account and the proper mother wavelet should be preferred in order to use the wavelet transform efficiently.

Discrete wavelet transforms (DWT) have been exposed to be useful for image analysis, due to wavelets having finite length which offers the frequency, spatial locality and efficient implementation. Typical 2D-DWT involves several hierarchies of decomposition and uses a pair of high-pass and low-pass filters derived from wavelet functions to decompose the original signal into one approximation subband and three detail subbands. The decomposition procedure is recursively applied to the approximation subband to create the next level of the hierarchy. If an orthonormal wavelet basis has been preferred, the coefficients calculated are independent and have a distinct feature of the original signal. The main cause is that the efficient execution of 2D-DWT requires applying a filter bank along the rows and columns of an image. Due to separability of the filters, the separable 2D-DWT is strongly oriented in the horizontal and vertical directions. This creates it hardly feasible to extract texture features from the wavelet coefficients. The 2-D DWT analyzes an image across rows and columns in such a way as to separate horizontal, vertical and diagonal details. In the first stage the rows of an $N \times N$ are filtered using a high pass and low pass filters. In the second stage 1-D convolution of the filters with the columns of the filtered image is applied. This directs at each level to 4 different subbands HH, HL, LH and LL. The LL is filtered again to obtain the next level representation.

The basic assumption with energy as a feature for texture discrimination is that the energy distribution in the frequency domain recognizes a texture. Further providing suitable retrieval performance from big database, energy based approach is partially supported by physiological studies of the visual cortex, which was presented by Hubel & Wiesel (1962), Daugman (1980). Manjunath & Ma (1996), Kokare et al (2004) have shown that the retrieval performance of energy feature parameter was forever found to be better than that of using other features. The texture database used in our experiment consists of 500 different images from the cancer imaging archive database. Size of each image is $512 \times 512$. Only gray-scale levels of the images were used in the experiments. Since we define similar images from a particular original one, we have selected images whose visual properties do not change too much over the image. Each image from database is decomposed using DWT. The analysis was performed up to third level of decomposition.

The energy and standard deviation of wavelet subband is computed by using equations (1) and (2) as follows

$$\text{Energy} = \frac{1}{m \times n} \sum_{i=1}^{M} \sum_{j=1}^{N} \left| X_{ij} \right| \tag{1}$$

$$\text{Standard Deviation} = \left[ \frac{1}{m \times n} \sum_{i=1}^{N} \sum_{j=1}^{M} (X_{ij} - \mu_{ij})^2 \right]^{\frac{1}{2}} \tag{2}$$

where M × N is the size of wavelet subband, Xij is wavelet coefficient and kμ is mean value of the kth subband. Length of the feature vector is equivalent to (No. of subbands × No. of feature parameters used in grouping) elements. For making of the feature database above two features are computed for all the 500 MRI cancer images and these feature vectors are stored in the feature database.

## 4. FUZZY C MEANS ALGORITHM

Fuzzy clustering is a dominant unsupervised scheme for the study of data and structure of models. In several situations, fuzzy clustering is more natural than hard clustering. Objects on the boundaries between some classes are not required to completely belong to one of the classes, but relatively are assigned membership degrees between 0 and 1 representing their limited membership. Fuzzy c-means algorithm is most commonly used and Fuzzy c-means clustering was first reported in the literature for a special case (m=2) by Joe Dunn in 1974. The common case (for any m greater than 1) was developed by Jim Bezdek in his PhD thesis at Cornell University in 1973. It can be enhanced by Bezdek in 1981. The FCM employs fuzzy partitioning such that a data point can belong to all groups with singular membership grades between 0 and 1.

### 4.1 Algorithm

1. Initialize A = [$a_{ij}$] matrix, $A^{(0)}$
2. At *k*-step: calculate the centers vectors $C^{(k)} = [c_j]$ with $A^{(k)}$

$$C_i = \frac{\sum_{j=1}^{n} a_{ij}^{m}}{\sum_{j=1}^{n} a_{ij}^{m}} \sum_{i=1}^{M} \left| X_{ij} \right|$$

3. Update $A^{(n)}$, $A^{(n+1)}$

4. $d_{ij} = \sqrt{\sum_{i=1}^{n} (x_i - c_i)}$ $\qquad u_{ij} = \dfrac{1}{\sum_{k=1}^{c} \left( \dfrac{d_{ij}}{d_{kj}} \right)^{2/(m-1)}}$ $\qquad u_{ij} = \dfrac{1}{\sum_{k=1}^{c} \left( \dfrac{d_{ij}}{d_{kj}} \right)^{2/(m-1)}}$

$$\left\| A(k+1) - A(k) \right\| < \in$$

5. If ||A(*k* + 1) – A(*k*)||<∈ then stop. Otherwise return to step 2.

Here m is any real number greater than 1,

$a_{ij}$ is the degree of membership of $x_i$ in the cluster $j$

$x_i$ is the ith of d-dimensional measured data,

$c_j$ is the d-dimension center of the cluster.

This fuzzy *c*-means algorithm works by conveying membership to each data point equivalent to each cluster center on the basis of distance between the data point and the cluster center. More the data is near to the cluster center and its membership towards the particular cluster center. Obviously, summation of membership of every data point should be equal to one. After every iteration membership and cluster centers are simplified according to the formula.

## 5. EUCLIDEAN DISTANCE CLASSIFICATION

The similarity measure by a given query image involves searching the database for similar wavelet coefficients as the input query. ED is suitable and effective method over any other distance measurements. A query pattern is any one of the patterns obtained from image database. This pattern is processed to compute the feature vector in the same manner as discussed in results and retrieval accuracy section.

**Steps for Feature Extraction and Similarity Matching**

1. Each image is decomposed using Wavelet.
2. Features such as energy and standard deviation are calculated from each of these wavelet subbands for all 500 MRI images and are stored in the database for the purpose of retrieval.
3. Obtain energy and standard deviation for database images and query image.
4. Fuzzy C-means is applied for clustering.
5. Distance between the query image and each image in the database is calculated using their feature vectors.
6. Sort ascending order of combined Energy and Standard Deviation features.
7. Top 20 relevant retrieved images are listed in GUI.

## 6. RESULTS AND RETRIEVAL ACCURACY

This section verifies the performance of the proposed approach using wavelet and fuzzy c-means with ED. Better retrieval rate has been obtained by using the proposed method. Implementation: The proposed CBIR system is implemented using MATLAB image processing tool box. In the execution, we use an Intel i3 processor. In order to test the efficiency of our proposed work, we experiment with 500 medical images. These images have been classified in to brain, breast, prostate and phantom category each of size 125. The GUI designed in this connection has been used database addition, browsing query image and searching similar images from database.

The precision and recall rates are widely used to evaluate the retrieval efficiency of the proposed method (Subrahmanyam Murala et al 2012). Precision is defined as the ratio of the number of retrieved relevant images to the total number of retrieved images (Zhang & Ye 2009). Precision is defined in Equation (3) and expressed in

$$\text{Precision} = \frac{\text{No. of relevant images retieved}}{\text{Total no. of images retieved}} \tag{3}$$

For the query image $I_q$, the precision is expressed as follows

$$P(Iq, n) = \frac{1}{n}\sum_{i=1}^{|DB|} \delta((\phi(I_i), (\phi(I_q)) \; |\mathrm{Rank}\,(I_i, I_q) \leq n| \tag{4}$$

where *n* indicates the number of retrieved images and |DB| is the size of the image database. Rank ($I_i$, $I_q$) returns the rank of image $I_i$ (for the query image $I_q$) among all the images of |DB| is shown in equation (5).

$$\delta((\phi(I_i),\phi(I_q)) = \begin{cases} 1, \phi(I_i) = \phi(I_q) \\ 0, else \end{cases} \tag{5}$$

Recall is defined as the ratio of the number of retrieved relevant images to the total number of relevant images in the whole database (Zhen et al.,2009). Recall is defined in equation (6) and expressed in equation (7)

$$\mathrm{Recall} = \frac{\text{No. of relevant images retrieved}}{\text{Total No. of images in the DB}} \tag{6}$$

For the query image $I_q$, the recall is defined as

$$R(I_q, n) = \frac{1}{N_G}\sum_{i=1}^{|DB|} \delta((\phi(I_i),\phi(I_q))\left|Rank(I_i, I_q) \leq n\right| \tag{7}$$

The average precision and the Average Retrieval Rate (AVRR) for the whole database image are computed using equation (8) and (9).

$$\mathrm{Pavg} = \frac{1}{|DB|}\sum_{i=1}^{|DB|} P(I_i, n) \tag{8}$$

$$\mathrm{AVRR} = \frac{1}{|DB|}\sum_{i=1}^{|DB|} R(I_i, n) \tag{9}$$

Where P ($I_i$, *n*) is a Precision rate of the image $I_i$ , R ($I_i$, *n*) is a Recall rate of the image $I_i$

where the rank of any of the retrieved image is defined to be its position in the list of retrieved image is one of the relevant images in the database. The rank is defined to be zero therwise. $N_c$ is the number of relevant images in the database.

The top hundred retrieved images for the MRI brain, breast, prostate and phantom database images are considered for validating the performance of the proposed technique. From table 1 it can be noted that the proposed approach has good average precision over existing approaches. Table 2 shows comparison of the average recall of the proposed method with existing methods like DWT and RCWF with CD and DT-CWF with PCA.

**Table 1**
**Comparison of the average precision for the proposed method with existing methods for top hundred matches**

| *No. of Top images considered* | *Average Precision for Proposed Approaches* | *Average Precision for Existing Approaches* | |
|---|---|---|---|
| | *Wavelet+FUZZY C-Means* | *DT-CWF+PCA* | *DWT + RCWF* |
| 10 | 1 | 1 | 1 |
| 20 | 0.90 | 0.91 | 0.90 |
| 30 | 0.87 | 0.86 | 0.85 |
| 40 | 0.81 | 0.80 | 0.79 |
| 50 | 0.79 | 0.78 | 0.77 |
| 60 | 0.75 | 0.73 | 0.72 |
| 70 | 0.74 | 0.72 | 0.70 |
| 80 | 0.67 | 0.67 | 0.66 |
| 90 | 0.64 | 0.63 | 0.61 |
| 100 | 0.61 | 0.61 | 0.59 |

**Table 2**
**Comparison of the average recall for the proposed method with existing methods for top hundred matches**

| *No. of Top images considered* | *Average Recall for Proposed method (%)* | *Average Recall for Existing methods (%)* | |
|---|---|---|---|
| | *Wavelet + PCA + MD* | *GLMeP* | *DWT + RCWF +CD* |
| 10 | 73 | 73 | 70 |
| 20 | 76 | 75 | 73.5 |
| 30 | 78 | 77.6 | 75.8 |
| 40 | 78.2 | 78 | 76.2 |
| 50 | 78.5 | 78.4 | 76.5 |
| 60 | 79 | 78.9 | 76.9 |
| 70 | 80 | 79.2 | 77.2 |
| 80 | 80.8 | 79.6 | 77.6 |
| 90 | 81 | 79.8 | 77.8 |
| 100 | 81.5 | 80 | 78 |

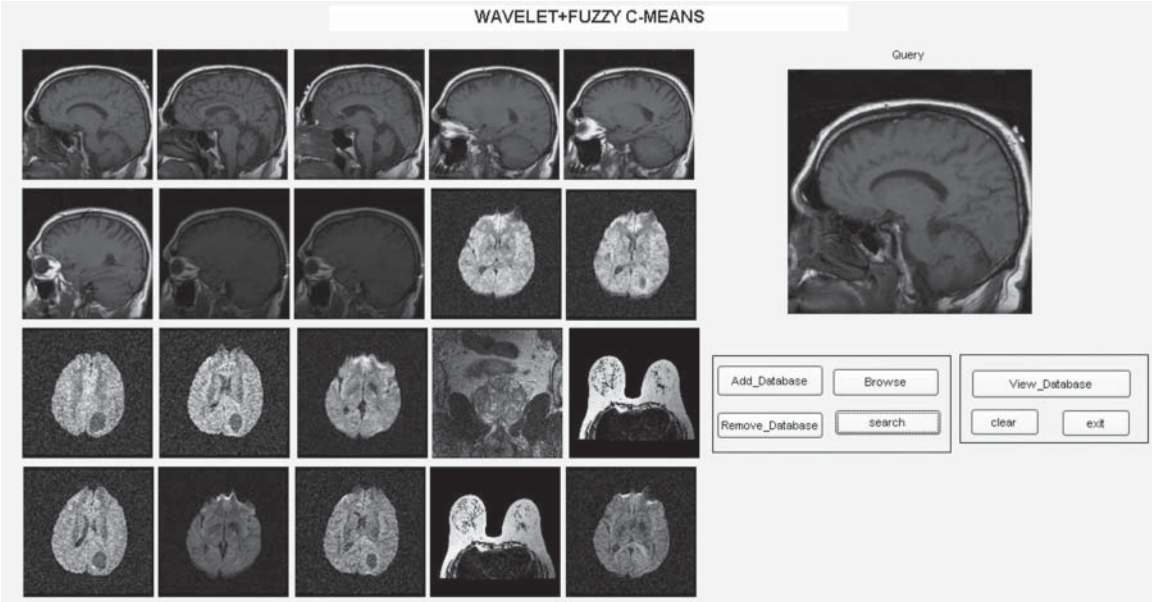


**Figure 3. Proposed method**

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