MIRS: Museum Image Retrieval System using Most Appropriate Low-Level Feature Descriptors

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Abstract

The main component of Content Based Image Retrieval is a feature extraction, where automatically extracted a low-level features (color, texture and shape). In this paper, several features extraction methods are explored to examine their effectiveness in retrieving images including Color Histogram, Color Layout Descriptor and Color Moment descriptors to represent the color feature. Texture is represented by Gray Level Co-occurrence Matrix, Local Binary Pattern and Gabor filter descriptors. Shape is represented by Hu's seven invariant moments and canny edge detection descriptors. A new approach to select the most appropriate descriptors to represent the image as uniquely and accurately using the average of success method is presented. Six transformations is applied to 100 original images of Iraqi National Museum of Modern Art collection to demonstrate experimentally the efficacy of the proposed approach and promising results are reported.

Keywords: *CBIR, Feature extraction, Low-Level features, Feature selection, Average of success method*

1. Introduction

Digital image libraries are becoming more common and widely used as visual information is produced at a rapidly growing rate. Nowadays creating and storing digital images is easy and getting more affordable all the time as the needed technologies is maturing and becoming eligible for general use. As a result, the amount of data in visual form is increasing and there is a strong need for effective ways to manage and process it.

Two methods to retrieve the image, the traditional method named Text-Based Image Retrieval (TBIR) is done by annotated the images using keywords annotation. There are three main difficulties with this method, firstly, the large amount of manual effort required in developing the annotations, secondly, the differences in interpretation of image contents, and finally, the inconsistency of the keyword assignments among different indexers [1].

Institutions that have large image collections, such as museums, often faced with the problems of loss the metadata, such as image file name, actor name, etc. The lack of image metadata reduces its importance, and the institutions are often asked to retrieve the desired image, using only the visual content as query. Therefore, using the second method Content-Based Image Retrieval (CBIR) as an alternative mechanism. CBIR was proposed in the early 1990's to overcome the difficulties of the pure annotation-based approach [2]. It is defined as any system that helps to retrieve and organize digital image archives based principally on low-level visual features such as color, texture and shape which automatic extraction methods are available [3].

CBIR uses for many applications like crime prevention, security check, finger print or retina scanning for access privileges. Medical diagnosis, trademark image registration, and museum images. IBM's QBIC system has received extensive trials in managing art library databases [4], and has proved an extremely useful browsing tool even if its retrieval effectiveness has been limited. In [5] they applied CBIR techniques to the management of image and video data relating to a Hindu temple in India. Their article highlights both the opportunities and problems associated with cultural heritage applications of CBIR.

The main component of CBIR is a feature extraction process, to extract set of different features automatically, then stored these features in the Database as a Feature Vectors (DFVs) to mapping them into new space called feature space to using it for similarity measurement between query image and database images by comparing the FV differences [6,7]. To increase the efficient of image retrieval, selecting the accurate features that represent the images as uniquely and accurately as possible.

Most of CBIR systems depend on one of low image feature (color, texture, and shape) in each retrieval process, since each feature extracted from images just characterizes certain aspect of image content, it is very difficult to get satisfactory retrieval results, so design and develop CBIR based on selection of appropriate relevant features to yield better retrieval performance be the optimal solution to achieve a

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very good retrieval. [8, 7]. Our research presents the design and implementation of an efficient Museum Image Retrieval System (MIRS) for the Iraqi National Museum of Modern Art based on select the most appropriate image features that give a high accuracy retrieval through the matching process between the original museum image and the query image with many transformation (image rotation, image cropping, image nosing, etc.).
In MIRS, a comparative study is presented to select the accurate color feature among many color descriptors like Color Histogram (CH), Color Moment (CM), and Color Layout Descriptor (CLD). For selecting accurate texture feature among many descriptors that used in analyzing the texture property of the image like Local Binary Pattern (LBP), Gabor Filter (Gab), and Gray Level Co-Occurrence Matrix (GLCM) and also for selecting accurate shape feature, Canny Edge Detector (CED) and Hu's seven invariant moments.

2. Typical Content-Based Image Retrieval (CBIR)

Typically, CBIR consist of three phases as show in Fig (1). Firstly, the off-line phase including, image data sets collection, features extraction process to extract the feature descriptors which represent the FV and store them in the database to represent the DFVs. Secondly, the on-line phase including, images database selection, query image selection, then extract Query Feature Vector (QFV). Finally, the retrieval phase including, loading DFVs, compute the similarity distance between QFV with all the DFVs using one of similarity measure, then sort all distance values ascending to display the images with zero or lowest distance value which represent the most similar images [9].

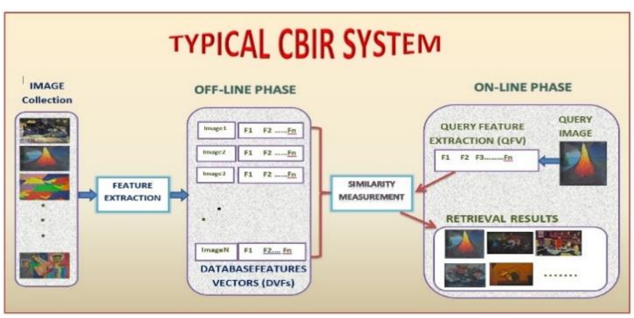

Fig 1: Typical CBIR system

3.Proposed Museum Image Retrieval System (MIRS) Architecture

An overview of the process steps of proposed system to obtain an efficient matching-based visualization from a museum image collection is shown in Fig (2).

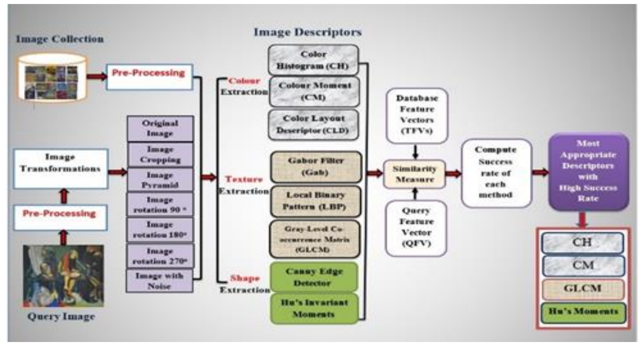

Fig 2: Block diagram of MIRS

3.1 Pre-Processing Process

Pre-processing is a primary process in proposed MIRS and required to be done on the original image of Iraqi National Museum of Modern Art collection were acquired using digital camera because the captured image may not be clear in resolution. An image can be pre-processed by cutting out all the image margins and image resize (resize the images; convert all various image window size into uniform window size) .This will be help in processing the image analysis. Fig (3) represent some examples of Iraqi National Museum of Modern Art collection before and after pre-processing process.

a b

Fig 3: Examples of Iraqi National of Modern Art collection
a: before Pre-processing process b: after Pre-processing process

3.2 Feature Extraction Process

The main component and the initial and critical stage of any CBIR system is the feature extraction process which is define as a process of automatically extract visual set of low‐level features such as color, texture and shape as FV and mapped into a new space named the feature space for the purpose of CBIR in retrieval and indexing [10, 7]. In our proposed MIRS, color, texture and shape features will be extracted as global features. Below is a list of features, what they measure, and how to extract them.

3.2.1 Color Feature

Color is the most basic quality of the visual contents, therefore it is possible to use the image colors to describe and represent an image. Color is one of the commonly and important low-level feature that is widely used in CBIR systems because of the simplicity of extracting it comparing with texture and shape information and it is very effective for searching and indexing in the database. Also it is comparatively robust to background complication and independent of orientation and image size [11, 12].

3.2.1.1 Color Histogram (CH)

Color Histogram (CH) descriptor is the most commonly used as image feature because it is easy to compute and it represents a compact description of the color content inside an image, and statistically, it gives the distribution of the number of pixels in an image representing a particular color and denotes the joint probability of the intensities of the three color channels (R=Red, G=Green, and B=Blue) of RGB color space. Color range is between 0 and 255 in each of the color bands, in this work, each CH quantizes the color space into 64 bins, where the color quantization is useful for reducing the calculation cost [10, 12, 13]. Formally, CH for a given image is defined as:

$$CH(I) = \{H(0), H(1), \ldots H(i), \ldots H(N)\} \quad (1)$$

Where i represent the color in CH and H(i) represents the number of pixels of color i in the image I, and N is the number of bins used in CH. For comparing the histogram of different sizes, color histogram should be normalized. The normalized CH' is given as [14]:

$$CH' = H / P \quad (2)$$

Where, p is the total number of pixels in image. The length of FV of CH is 64 dimension.

3.2.1.2 Color Moment (CM)

Color moments (CM) method has the lower computational complexity and lowest feature vector dimension. Therefore, CM have been successfully used in many image retrieval systems [15, 16, 17]. In proposed MIRS, we extract the first three moments from each color channel (mean, standard deviation and the variance) to describe the color distribution of an image.

3.2.1.2.1 Mean Color Descriptor (f_M)

The mean color descriptor can be represented by a color vector:

$$f_M = (\bar{M}_R, \bar{M}_G, \bar{M}_B) \quad (3)$$

The color vector of equation (3) is extracted by measuring the mean color for each channels (R, G, B) through equations (4) to (6):

$$\bar{M}_R = \frac{\sum_{i=1}^{n} R_i}{n} \quad (4)$$

$$\bar{M}_G = \frac{\sum_{i=1}^{n} G_i}{n} \quad (5)$$

$$\bar{M}_B = \frac{\sum_{i=1}^{n} B_i}{n} \quad (6)$$

3.2.1.2.2 Standard Deviation Descriptor (*fs*)

The color moment descriptor based on standard deviation can be represented by a color vector given in equation (7):

$$f_{S^2} = (S_R, S_G, S_B) \quad (7)$$

Which is extracted by measuring the standard deviation of color for each channel (R, G, B) using equations (8) to (10), respectively:

$$S_R = \sqrt{\frac{\sum_{i=1}^{n}(r-\bar{r})}{n}} \quad (8)$$

$$S_G = \sqrt{\frac{\sum_{i=1}^{n}(g-\bar{g})}{n}} \quad (9)$$

$$S_B = \sqrt{\frac{\sum_{i=1}^{n}(b-\bar{b})}{n}} \quad (10)$$

3.2.1.2.3 Variance Descriptor (*fv*)

The color moment descriptor is based on variance, which can be represented by computing the square of the standard deviation. Therefore, the index entry for one image consists of:

Index size = number of color channels X 3 floating point numbers ……....................……(11)

Thus, we have to store 9 floating point numbers per image. So, the feature vector f_{CM} is given by:

$$f_{CM} = [f_M \;\; f_S^2 \;\; f_V] \quad (12)$$

3.2.1.3 Color Layout Descriptor (CLD)

The Color Layout Descriptor (CLD) captures the spatial layout of the representative colors in an image. Representation is based on coefficients of the Discrete Cosine Transform (DCT) on a 2-D array of local representative colors in Y or Cb or Cr color space. This is a very compact descriptor being highly efficient in fast browsing and search applications. Our implementation is based on [18, 19], the extraction process of CLD consists many stages including; divide the RGB image to 64 blocks to guarantee the invariance to scale or resolution, select any method to representative the color on each block. The average of color pixels in a block is presented, since it is simpler and in general, the description accuracy is

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sufficient, convert the RGB color space to the YCbCr using the equations (11-13) as:

Luminance Y=0.299*R+0.587*G+0.114*B – 128…..(13)
.
Blue chrominance Cb=0.169*R–0.331*G+0.500*B...(14)

Red chrominance Cr=0.500*R–0.419*G– 0.081*B…(15)

The luminance (Y), blue and red chrominance (Cb and Cr) are transformed by 8x8 DCT, so three sets of 64 DCT coefficients are obtained. In order to group the low frequency coefficients of the 8x8 matrix, zigzag scanning is performed with these three sets of 64 DCT coefficients. Finally, the output is three set of [8x8] zigzag scanned matrices of 64 coefficients (DCTY, DCTCb, DCTCr) represent the CLD descriptor of the input image. Where the matching process will be used to compute the distance between the CLD of the query image {DY, DCb, DCr} with the CLDs of the target image { DY'', DCb'', DCr'' } to evaluate if they are similar. The distance between these descriptors can be computed using equation (16):

$$\boldsymbol{D} = \sqrt{\sum_i \boldsymbol{W}_{yi}(\boldsymbol{DY}_i - \boldsymbol{DY}'_i)^2} + \sqrt{\sum_i \boldsymbol{W}_{bi}(\boldsymbol{DCb}_i - \boldsymbol{Db}'_i)^2} + \sqrt{\sum_i \boldsymbol{W}_{ri}(\boldsymbol{DCr}_i - \boldsymbol{DCr}'_i)^2} \text{.............................} \quad (16)$$

Where DY_i, DCb_i, and DCr_i denote the ith coefficients of Y, Cb, Cr color component, and wy_i, wb_i, and wr_i are the weighting values for the ith coefficient, respectively. The lower value of D the higher similarity between the query image and database images.

3.2.2 Texture Feature

Texture feature, also, has been one of the most important and a robust low-level descriptor for image in recognition and retrieval applications; Image Texture gives us information about the spatial arrangement of color or intensities in an image or selected region of an image .It is one of the visual features used in CBIR to represent the contents of the image effectively in order to search and retrieve similar areas [20].

Generally, there are two basic classes of texture descriptors that exist for identifying and manipulating the texture [13]. The first class called statistical domain which sees an image texture as a quantitative measure of the arrangement of intensities in a region. In general this approach is easier to compute and it is more widely used, since natural textures are made of patterns of irregular sub elements such as (Gay-Level Co-occurrence Matrix (GLCM), Local Binary Pattern (LBP) which describe textures [21]. The second class called Frequency domain sees an image texture as a set of primitive texels in some regular or repeated pattern such as Gabor (Gab) filter. In our proposed MIRS, GLCM and LBP are extracted as a proper candidates from statistical model, where using Gab as a proper candidate from frequency domain.

3.2.2.1 Local Binary Pattern (LBP)

Local Binary Pattern (LBP) operator was produced in [22]. It is basically a good scale descriptor that gets small texture details, one of the best performing texture descriptors, and it has since been found to be an important and a powerful feature of analysing image textures, texture classification of a digital (gray scale) image. The principle of LBP is based on a binary code created by dividing the image into several small regions (cells). The operator assign a label to every pixel of an image by works with the eight neighbors (3×3 neighbors) of a pixel using the center pixel as a threshold and compares the threshold with all the neighbors' pixels. Formally, the LBP operator takes the following form:

$$\mathbf{LBP}(\mathbf{x_c}, \mathbf{y_c}) = \sum_{\mathbf{n=0}}^{\mathbf{7}} \mathbf{2^n}\ \mathbf{s}(\mathbf{i_n} - \mathbf{i_c}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots..(\mathbf{17})$$

Where n runs over the 8 neighbours of the central pixel c, i_n and i_c are the gray-level values at n and c, and s(..) is labeled with 1 if s(..) ≥ 0, otherwise is labeled with 0. The LBP code for the centre pixel is then produced by concatenating the eight ones or zeros to a binary code, then converted it to the decimal number to represent the new centre value. Finally, compute the histogram of the LBP labels over a region, then concatenated normalized histograms into a single efficiently feature histogram representing the image texture feature. Fig (4) illustrates the basic LBP operator for texture feature extraction.

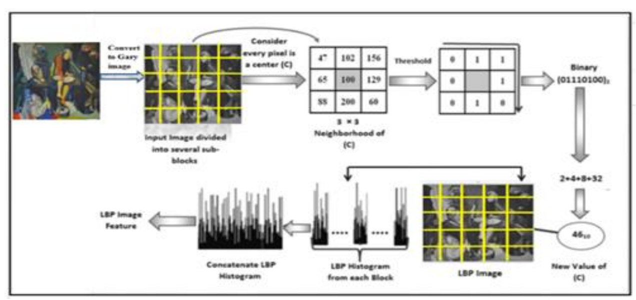


Fig 4: Basic LBP operator

3.2.2.2 Gray-Level Co-occurrence Matrix(GLCM)

Gray Level Co-Occurrence Matrix (GLCM) was introduced by [23]. GLCM has proved to be a common method of extracting second order statistical texture feature from an image. Many factors it should be specified before computing GLCM feature, which are [24, 25, 26]; the spatial relationship (angle θ) which is defined as the pixel of interest (reference) pixel, and the neighbour pixel which is limited to (0º, 45º, 90º, and 135º), displacement d=(dx, dy) between the reference and its neighbour pixel over the image (d could take a value of 1,2,3,…n), and the number of gray levels (G), atypical value of G is 4, 8, 16 or 32 and the size of GLCM is determines by this number. After determined these factors in the algorithm, the output is 2D (square) dependence GLCM matrix. There are multiple number of GLCM matrices depending on different values of *d* and θ. Fig (5) illustrated the GLCM matrix formulation with example for four different gray levels. Fig (6) illustrated the common angles given the pixel distance D.

neighbour pixel value / reference pixel value	0	1	2	3
0	0,0	0,1	0,2	0,3
1	1,0	1,1	1,2	1,3
2	2,0	2,1	2,2	2,3
3	3,0	3,1	3,2	3,3

Fig 5: illustrated the GLCM matrix

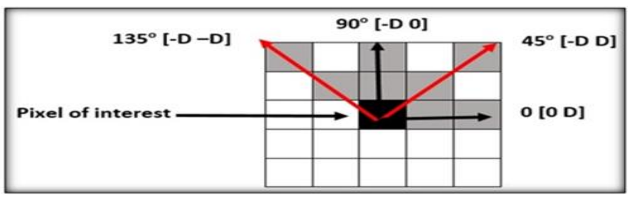
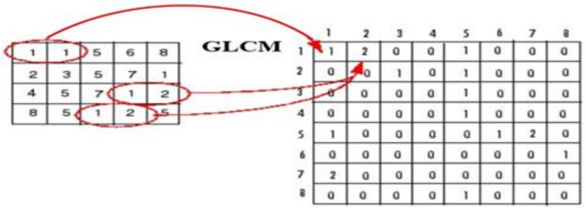


Fig 6: GLCM matrix directions

The element P (i, j | d, ɵ) of GLCM is the sum of the number of times that the pixel with intensity (gray-level) value i occurred in the specified certain relationship to a pixel with value j in the input image. Due to the information getting from the single GLCM (using one direction) might not be enough to describe the texture feature of an image, therefore, in this paper, several experiments were conducted using various angle to create multiple GLCMs for a single input image by scanning the intensity of each pixel and its neighbor, defined by displacement *d*=1. As a result the system produce high accuracy with the best angle selection experimentally (45º together with 135º) and G = 8 to compute the GLCM feature. A new matrix is formed by summation these matrices which is represent the GLCM feature vector with 64-dimention (8-by-8). Fig (7) show an example of creating GLCM Matrix for eight different gray levels.



(a) (b)

Fig. 7 (a). Image matrix; (b): GLCM matrix

3.2.2.3 Gabor filtering

Gabor filter is a technique that extracts texture information from an image. In this research, a 2-dimensional Gabor function proposed by [27] is used. Gabor filters are a set of wavelets and each wavelet capturing energy at a certain frequency (scale) and direction. The energy of the filtered image is used as the texture features. For a given image I(x,y) with size PXQ, its discrete Gabor wavelet transform is given by a convolution:

$$G_{mn}(x,y) = \sum_s \sum_t I\,(x-s, y-t)\,\Psi^*_{mn}(s,t) \ldots\ldots\ldots(18)$$

Where, s and t are the filter mask size variables, and is the complex conjugate of ψ_{mn} which is a class of self-similar functions generated from dilation and rotation of the following mother wavelet:

$$\frac{1}{2\pi\sigma_x\sigma_y}\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)\right].\exp(j\,2\,\pi w_x)\ldots\ldots\ldots(19)$$

Where W is called the modulation frequency. ψ(x, y) is a Gaussian modulated by a complex sinusoid [5]. The self-similar Gabor wavelets are obtained through the generating function:

$$\Psi_{mn}(x,y) = a^{-m}\Psi\,(\bar{x},\bar{y}) \ldots\ldots\ldots(20)$$

Where m and n specify the scale and orientation of the wavelet respectively, with m = 0, 1,…M-1, n = 0, 1,...N-1, and M is the number of scales, N is the number of orientations (translations):

$$\bar{x} = a^{-m}\,(x\cos\theta + y\sin\theta)\ldots\ldots\ldots(21)$$

$$\bar{y} = a^{-m}\,(-x\sin\theta + y\cos\theta)\ldots\ldots\ldots(22)$$

Where a>1 and $\theta = \frac{n\pi}{N}$; *t* he variables in the above equations are defined as follows:

$$a = (Uh/\,Ul\,)^{\frac{1}{M-1}}\ldots\ldots\ldots(23)$$

Where, ***a*** is the scale factor, Ul denote the lower frequency and Uh denote the upper frequency of interest:

$$\mathrm{W_{m,n}} = \mathrm{a^m} U_l \ldots\ldots\ldots(24)$$

$$\sigma_{x,m,n} = \frac{(a+1)\sqrt{2\ln_2}}{2\pi a^m (a-1)U_l}\ldots\ldots\ldots(25)$$

$$\sigma_{y,m,n} = \frac{1}{2\pi\tan\left(\frac{\pi}{2N}\right)\sqrt{\frac{U_h^2}{2\ln 2}-\left(\frac{1}{2\pi\sigma_{x,m,n}}\right)^2}}\ldots\ldots\ldots(26)$$

The values of σ_x and σ_y represent the spatial extent and bandwidth of the filter in x and y directions respectively. Different orientation at different scale were using to apply Gabor filer, the output is an array of magnitudes which represent the energy content at different scale and orientation of the image. To represent the texture feature, following mean μ_{mn} and standard deviation σ_{mn} of the magnitude of the transformed coefficients are used:

$$\boldsymbol{\mu_{mn}} = \frac{\boldsymbol{E(m,n)}}{\boldsymbol{PxQ}} \ldots\ldots(27)$$

$$\boldsymbol{\sigma_{mn}} = \frac{\sqrt{\sum_x \sum_y |(G_{mn}(x,y))| - \mu_{mn}}}{PxQ} \ldots\ldots(28)$$

Texture representation is created using μ_{mn} and σ_{mn} as the feature components. M scales and N orientations are used and the feature vector is given by:

$$f = (\mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01}, \ldots, \mu_{(M-1)(N-1)}, \sigma_{(M-1)(N-1)}).$$

For Ul = 0.05, Uh = 0.4, M = 3 and N= 4. These values are used later in the experiments. Thus we have 12 Gabor filters feature vector at 3 scales and 4 orientation.

3.2.3 Shape Feature

The shape of an object is a basic and important visual feature. In general, shape description and representation techniques can be categories into two classes of methods: contour shape-based that uses to extract only the outer shape's boundary information and region shape-based methods which employs the whole shape region [28]. In this paper, using canny edge detection (CED) as boundary-based shape and Hu's seven invariant moments (Hu) as a compact and an effective region-based shape descriptor are among the common shape representations.

3.2.3.1 Canny Edge Detection (CED)

The multi-scale edge map is formed by finding the edges using the canny edge algorithm (CED) [29].The process of CED extraction is:

1. Smooth the image with a Gaussian filter to reduce unwanted details and textures and noise.

$$g(m,n) = G_\sigma(m,n) * f(m,n) \ldots\ldots (29)$$

Where

$$G_\sigma = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{m^2+n^2}{2\sigma^2}\right] \ldots\ldots(30)$$

2. Compute gradient of g(m,n) using any of the gradient operators to get:

$$M(m,n) = \sqrt{g_m^2(m,n) + g_n^2(m,n)} \ldots\ldots(31)$$

and

$$\theta(m,n) = \tan^{-1}[g_n(m,n)/g_m(m,n)] \ldots\ldots(32)$$

Image edge is a matrix, their elements are 0, 1. Element 1 is object edge, and 0 is not. The algorithm tracks along these regions and eliminate any pixel which is not at the maximum. The gradient array is now further reduced by hysteresis. Hysteresis uses two thresholds *T1*, *T2*, if the magnitude is below *T1*, it is made a non-edge. If the magnitude is above *T2*, it is made an edge. And if the magnitude is between *T1 and T2*, then it is set to zero unless there is a path from this pixel to a pixel with a gradient above *T2*. Fig (8) show original image and edge image.

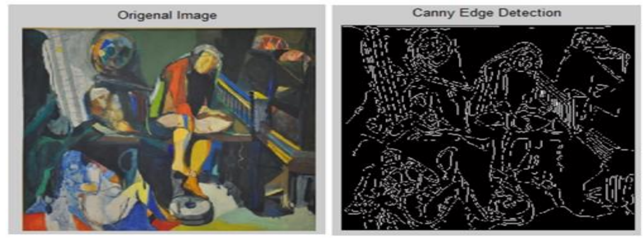


Fig 8: a: the original image; b: edge map by CED

3.2.3.2 Hu's Invariant Moments (Hu)

Invariant moment is one of the shape representation and presented for first time by Hu in 1962 [30]. Invariant moments have been extensively applied to image pattern recognition in a variety of applications because they are useful properties of being unchanged under image rotation, translation, and scaling [31]. Hu proposed and defined the following seven invariant moment. In this paper, we used these moments to compute the FV of shape descriptor. Therefore, the length of FV using Hu descriptor will be 7-Dimension.

$$I_1 = n_{20} + n_{02}$$

$$I_2 = (n_{20} + n_{02})^2 + 4n_{11}^2$$

$$I_3 = (n_{30} + 3n_{12})^2 + (3n_{21} - n_{03})^2$$

$$I_4 = (n_{30} + n_{12})^2 + (n_{21} - n_{03})^2$$

$$I_5 = (n_{30} - 3n_{12})(n_{30} - n_{12})[(n_{30} + n_{12})^2 - 3(n_{21} + n_{03})^2 + (3n_{12} - n_{03}) (n_{12} - n_{30})[3(n_{30} + n_{12})^2 - (n_{21} + n_{03})^2]$$

$$I_6 = (n_{20} - n_{02})[(n_{30} - n_{12})^2 - (n_{21} + n_{03})^2 + 4n_{11}(n_{30} + n_{12}) - (n_{21} - n_{03})]$$

$$I_7 = (3n_{21} - n_{03})(n_{30} - n_{12})[(n_{30} + n_{12})^2 - 3(n_{21} + n_{03})^2 + (n_{30} - 3n_{12})(n_{12} - n_{30})[3(n_{30} + n_{12})^2 - (n_{21} + n_{03})^2] \ldots\ldots (33)$$

Table (1) illustrate the results of Hu shape descriptor for one original image with translations of query image. We can see the Hu's values is invariant under image rotation and it differences is very simple with another transformations.

Translations of Query Image	Hu's Seven Invariant Moment						
	I1	I2	I3	I4	I5	I6	I7
Original Image	0.3137	0.0272	0.0001	0.0002	0	0	0
Image Rotate with 90°	0.3137	0.0271	0.0001	0.0002	0	0	0
Image Rotate with 270°	0.3137	0.0271	0.0001	0.0002	0	0	0
Image Rotate with180°	0.3137	0.0271	0.0001	0.0002	0	0	0
Image Cropping	0.3131	0.0302	0.0001	0.0001	0	0	0
Image Pyramiding	0.3131	0.027	0.0001	0.0002	0	0	0
Image with Salt & Pepper Noise	0.3164	0.0276	0.0001	0.0002	0	0	0

Table 1: Result of Hu's seven invariant moments for one image from museum image DB

4. The Proposed MIRS Algorithm

The proposed MIRS has two phases. First is to identify and extract the image features, by applying CH, CM, and CLD as a color features, LBP, Gabor filter, and GLCM as a texture features, Hu and CED as shape feature. The second phase is employed to compare the similarity distance between the query image (original image, different rotate image, cropping image, image pyramid, and noise image) with the all images in the museum images database, using the Euclidean distance. Where the Euclidean distance between QFV (f_q) and DFV (f_D) is:

$$d(f_q, f_D) = \text{sqrt}(\text{sum}((f_q - f_D).\text{^}2))\ldots\ldots\ldots\ldots\ldots\ldots(34)$$

The following steps are performed in the proposed MIRS system:

Step 1: Collect the museum images from the Iraqi National Museum of Modern Art databases.
Step 2: Apply pre-processing process as mentioned in section 3.1.
Step 3: Read museum images one by one.
Step 4: Extract all features as described in section 3.2 to get the FVs, then stored them as an index in the databases to get DFVs which represent the feature space.
Step5: Use the original museum image with all different rotation image, cropping image, image pyramid, and noise image as query image to extract all the image features mentioned in step (4) to get the QFV.
Step 6: Finally, The matching process between QFV with all DFVs is performed using Euclidean Distance measure to compute the distance values.
Step 7: Save the distance values for each query image.
Step 8: Sort the distance values in ascending order and the image with zero or smallest value is the most similar to the original image.
Step 9: Display the corresponding museum images.
Step 10: Compute the percentage of successful retrieval for each descriptor and for each query. The successful retrieval mean that retrieve the original museum image as the *first* image in the results list.
Step 11: Compute the average of the successful retrieval of all feature descriptors for each type of query.
Step 12: From step 11, we can select the appropriate feature descriptors (CH, CM as color features, GLCM as texture feature and Hu shape feature).

5. Experimental Setup

5.1 Image Data Set

The experimental results are evaluated over different collection of homogenous 100 images from Iraqi National Museum of Modern Art collection that utilized texture and color features. In this paper, color, texture and shape images are all taken from museum collection. The database contained old and modern photos, paintings, and drawings images. Fig (5) shows some samples of the original museum image employed in this research.

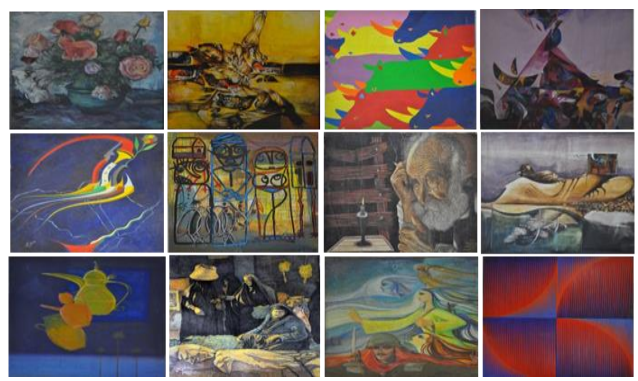


Fig 9: Samples Iraqi National Museum of Modern Art Image

To test MIRS, 100 original images were collected, each accompanied of 6 transformations, summing up to 700 images. The transformations were:

1. Three image rotations with 90, 180, and 270 degree.
2. Addition of a strong Salt and pepper noise; this noise refers as 'impulsive noise' which means that dark pixel over in the bright region as also bright pixels over in the dark region.
3. Image Pyramid; computes a Gaussian pyramid expansion for museum image by one level, then the size of image output is (2*M-1)-by-(2*N-1), where M and N represent the image dimensions
4. Image cropping is limited since it can be only remove pixels from the image periphery.

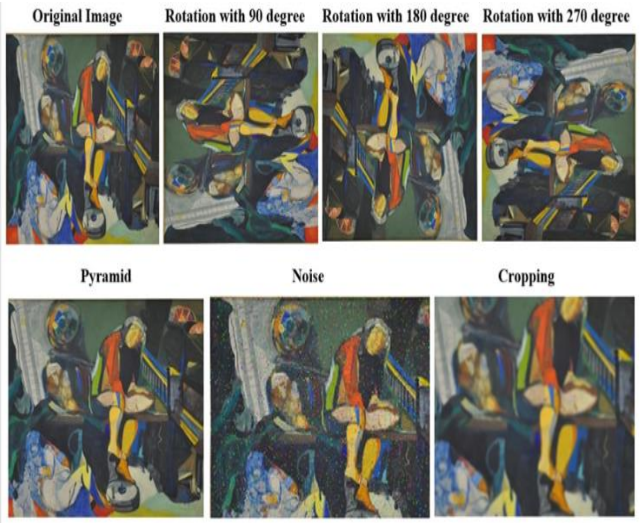


Fig 10: Samples of the possible transformations for the query image.

5.2 Performance Evaluation

The performance analysis of the proposed MIRS system is presented in this section. The experiment consisted in submitting each one of the transformed images as query, and collecting the most similar images, accordingly to each method. The retrieval results of MIRS was considered successful by the user if the original image was in the first rank of the returned set. Table 1 show the experimental results. We showed the percentage of successes of all feature extraction methods, classified by type of all transformation of the query.

Table 2: Success rate (average retrieval rate) of the methods (color, texture and shape Descriptors) for each type of query

Transformations of Query Image	The percentage of successful retrieval							
	Color Descriptor			Texture Descriptor			Shape Descriptor	
	CH	CM	CLD	Gab	Basic LBP	GLCM (45°+135°)	Canny edge detection	Hu's 7 invariant moments
Original Image	100	100	100	100	100	100	100	100
Image Rotate with 90 Degree	100	99	23	21	97	100	7	100
Image Rotate with 270 Degree	100	97	21	79	93	100	9	100
Image Rotate with180 Degree	100	98	25	26	94	100	16	100
Image Cropping	100	80	84	42	39	76	24	67
Image with Salt & Pepper Noise	98	60	100	76	5	92	45	66
Image Pyramid	100	97	100	86	17	29	100	95
The Average	99.71	90.14	64.71	61.43	63.57	85.29	43	89.71

The results showed that for all the transformations. CH, CM, GLCM, and Hu features performance was particularly excellent in the color, texture, and shape feature respectively, where the CLD, Gab, LBP, and CED features performance was particularly poor in color, texture and shape transformations respectively and was catastrophic under the some rotation, because this transformation completely modifies the values of these features. We can also see the noising is remarkable poor performance in the CM color feature, LBP texture feature, and Hu shape feature. Whilst, the Hu descriptor is useful feature of being unchanged under any image rotation. CED can't distinguish effectively the edge image rotation. Therefore and depending on these results we can select (CH, GLCM, and Hu) as the appropriate color, texture, and shape descriptors respectively based proposed MIRS.

6. Conclusion and Future Work

The key of design an effective image retrieval system is to select the accurate feature that represent the images as accurately as possible. In this paper, a MIRS for Iraqi National Museum of Modern Art images collection based on various techniques for most appropriate feature extraction and similarity measurement is presented. The experiment results also confirms the efficiency of proposed enhanced museum image retrieval system. The first stage of our proposed MIRS is the pre-processing stage which include cutting the image regions and image resize applied on all images database and query image. Many transformations like image rotation, cropping, pyramid, and noising process were applied on all original images to represent the query images in order to use them as the test set to examine the performance of MIRS. We have shown that our approach achieve the aim of proposed MIRS in selection a set of most appropriate descriptors, We observing the results in various queries, it is easy to ascertain in most of the queries, excellent retrieval results by retrieved the original image without metadata as the first image in the rank of the results list with a success rate of 99.71% of CH. This result indicate that color histogram has the advantages of quickness and not sensitive to image changes, such as cropping, rotation, etc. 90.14% of CM against 85.29% of GLCM and 89.71 % of Hu descriptors. From these results, we can conclude that the selection features by the proposed MIRS are appropriate for accurately retrieving the original museum images even in distortion cases such as cropping, rotation, and noise. Also by using the proposed MIRS system, we can decide on the best descriptor for each image entered into the system. Our current work, on high-performance by fuse these appropriate descriptors will allow as to get much more accurate results because the more features used, the more information the mostly perfect retrieval has to work with. Also, by using local features enables features algorithms to better handle scale changes, rotation, etc.

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