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New Feature Fusion Technique Based Museum Image Retrieval System

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ABSTRACT

Background: The key in accomplishing an effective retrieval system is to select the proper features that represent the images as uniquely and precisely as much as possible. The features selections have to be sufficient and discriminative in describing the content present in the image. To achieve these aims, most of **C**ontent **B**ased **I**mage **R**etrieval (**CBIR**) systems depend on one of low image feature (colour, 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 combination of appropriate relevant features to yield better retrieval performance be the optimal solution to increase the accuracy of image retrieval. In this paper, design and implement **C**ontent **F**usion **B**ased **I**mage **R**etrieval (**CFBIR**) system based on fuse individual feature is presented. **Objective:** The main objectives of proposed **CFBIR** system are; ***firstly***, retrieve the images based on individual feature in order to choose appropriate descriptors that represent the image as unique as possible. ***Secondly***, fuse these descriptors using ***Early fusion*** technique, in this method, the feature vector of each descriptor are fused to form a large single **F**eature **F**usion **V**ector (**FFV**) before matching process. **FFV** will be suffer from so called "curs of dimensionality", consequently, it is going to be very time-consuming for retrieve images. ***Thirdly,*** to overcome this problem, new feature fusion technique using **XOR** function is produce. **Results:** The experimental results are evaluated over a collection of 700 homogenous images including 100 original images of Iraqi National Museum of Modern Art collection with six transformation for each image which represent the query image to demonstrate experimentally the efficacy of the proposed system. **Contribution**: The experimental results showed that the Early feature fusion technique does improve the retrieval performance comparing with the results obtained by of using individual feature. Also, The proposed feature fusion technique has proved to be easy to implement with a highly efficient image retrieval and can be adopted as features fusion technique in many other more sophisticated retrieval systems.. **Conclusion:** Reported results show that the best colour extraction method is Colour Histogram (**CH**) descriptor; for texture method Gray Level Co-occurrence Matrix (**GLCM**) descriptor; and for shape is Hu's seven variant moments (**Hu's**) descriptor. For the combination of these descriptors using ***Early Feature Fusion*** technique gives the excellent result (**90.422%**) comparing with the individual descriptor. The effectiveness of the proposed ***New Feature Fusion*** technique is able to achieve high rate accuracy. The results were promising, as it increased the retrieval performance to become (**93.286%**).

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INTRODUCTION

The rapid development of multimedia allows for wide distribution of digital media data in various applications such as Medical imaging, museum image, trademark registration, Textiles industry, digital library, etc. The problem with existing and widely adapted method for text-based image retrieval are done manually have proven to be difficult, time consuming and insufficient. Therefore efficiently and effectively retrieve the desired images from large and varied image databases is now a necessity. This system is commonly known as Content-Based Image Retrieval (CBIR), which is defined as any system that helps to retrieve and organize digital image archives by their visual content. Feature Extraction (FE) process is a major component of CBIR, which automatically extract different low-level features such as colour, texture and shape, from database images, then stored these features in the database as Database Feature Vectors (DFVs) to mapping them into

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new space called feature space, then using this feature space values for similarity measurement between Query Feature Vector (QFV) and DFVs by comparing the feature vector differences (Kavitha, C., *et al*. 2011 and Mahdi, F., *et al*,2012).

The key in accomplishing an effective retrieval system is to select the proper features that represent the images as accurately and uniquely as possible. The features selection have to be sufficient and discriminative in describing the content present in the image. Most of CBIR systems depend on one of these features in each retrieval process, since each feature just characterizes certain aspect of image content, it is very difficult to get satisfactory retrieval results, so design and develop CBIR based on combination of appropriate relevant features to yield better retrieval performance be the optimal solution to achieve a very good retrieval (Fatin Abbas. Mahdi, and Abdulkareem Ibadi, 2014). For instance, IBM's QBIC (Faloutsos, C., *et al*, 1994) uses colour histograms, a texture descriptor and a moment-based shape feature, MIT's Photobook (Pentland, A., Picard, *et al*. 1996) uses 2D shape features, texture features and appearance features. To address the critical problem in CBIR to measure the image similarity based on multiple visual features, a new trend is the Features Fusion (FF) technique is necessary to represent the images as matchless as possible, and to extend the system ability for accuracy results. Recently, fusion of descriptors has become a trend for improving the performance in image and video retrieval tasks (Andrade, F., *et al*.(2012)). In this paper, design and implement Content Fusion Based Image Retrieval (CFBIR) system for Iraqi National Museum of Modern Art is presented. The objectives of this system are *firstly*, retrieve the images based on single feature in order to select the most suitable colour, texture, and shape descriptors that represent the image as unique much as possible by compute the average of success rate of retrieval results for each feature's descriptor. *Secondly*, in order to increase the efficiency of the system, general fusion method namely, Early Feature Fusion Technique (EFFT) was used to fuse these descriptors. In this method, the feature vector of each descriptor are fused to form a large single Feature Fusion Vector (FFV) before matching process. FFV will be suffering from so called "curs of dimensionality", consequently, it is going to be very time-consuming for retrieve the images. *Thirdly*, to overcome this problem, proposed new feature fusion technique using XOR function is produce. Colour is represented by cumulative Colour Histogram (CH) and Colour Layout Descriptor (CLD). To analysing the texture property of the image, Local Binary Pattern (LBP) and Gray Co-occurrence Matrix (GLCM) are used. Canny Edge Detector (CED) and Hu's seven invariant moments (Hu) are extracted to represent the shape feature.

The Proposed Content Fusion Based Image Retrieval (CFBIR) System:

The main objectives of proposed CFBIR system are; *firstly*, retrieve the images based on individual feature to choose the robust colour, texture, and shape feature descriptors that represent the images as unique as much possible. *Secondly*, to increase the accuracy of CFBIR performance, combining these descriptors using the general EFFT to form a large single Feature Fusion Vector (FFV) before matching process is presented. FFV is suffering from so called "curs of dimensionality", so, it is going to be very time-consuming for retrieving images. *Thirdly*, to overcome this problem, new feature fusion technique using XOR function is produce, and lastly, a comparative study between all results of proposed CFBIR system. Next section show these objectives in details.

Image Retrieve Based Individual Feature:

To choose the robust descriptors of image low-level (colour, texture, and shape) features based image retrieval system, three stages should be performance; Off-Line stage, On-Line stage, Descriptors Selection stage. The following sections illustrate all these stages in some detail, and for more details of each stage can be found in our previous work (Fatin Abbas. Mahdi and Abdulkareem Ibadi, 2014).

Off-Line Stage:

In this stage, two processes were applied on all images in the database to get the DFVs. These processes are; Pre-processing and Features Extraction (FE) process. Figure (1) show the block diagram of Off-Line stage.

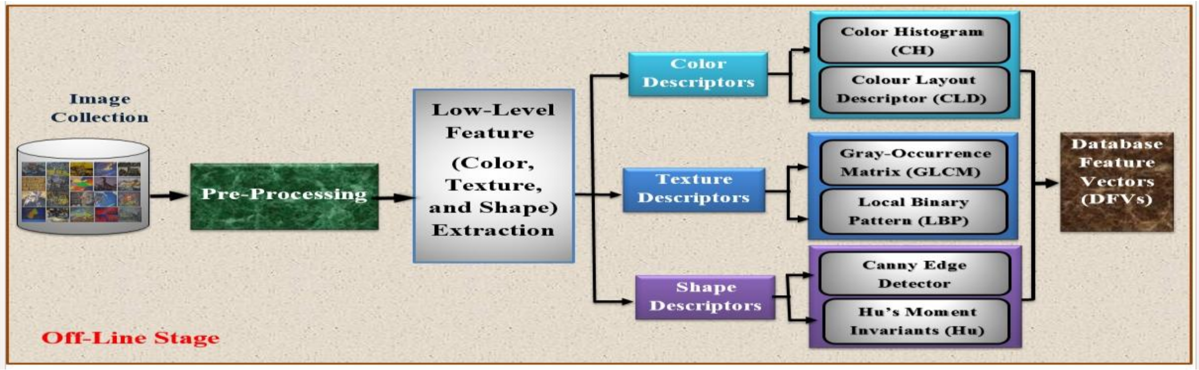

Fig. 1: Block diagram of Off-Line stage of proposed CFBIR system.

Pre-processing Process:

The first process of the proposed CFBIR system is the pre-processing step which it is necessary to be done for the original images of Iraqi national museum of modern art collection which have been obtained using a digital camera and may be not clear in the resolution and be irregular in shape. In this case, the image footnotes should be cutting. Another per-processing is image resize for all images to be in the same size. Figure (2) show some examples of Iraqi National Museum of Modern Art collection before and after pre-processing process.

(a) (b)

Fig. 2: Original of Iraqi National of Modern Art collection; a: Before Pre-processing process; b: after Pre-processing process.

Review of Feature Extraction Techniques:

Feature Extraction (FE) is the process of capturing visual content of an image for indexing and retrieval and it is the main component of any CBIR system. FE is the critical step that needs to be carried out very carefully for any retrieval or recognition system that uses pattern (sample) matching which increase the accuracy of system performance. In this paper, Colour, texture, and shape features will be extracted automatically from all museum database images, then store these features in the database to get the Database Feature Vectors (DFVs) then mapped them into a new space named the feature space for the purpose of CBIR in indexing and retrieval (Mahdi, F., *et al*, 2012).

***Colour feature*:**

Colour and its descriptors based representation is one of the significant low-level feature that is commonly used in CBIR systems for the simplicity of extracting it comparing with other image features and it is very efficient in indexing and searching in the image database (Alamdar, F., and Keyvanpour, M.R, 2011) and (Savvas A. *et al*, 2011).In this paper, Colour Histogram (CH) and Colour Layout Descriptor (CLD) descriptors are extracted to represent the colour feature:

Colour Histogram (CH):

The histogram of an image is defined by the probability mass function of the image intensities. In CBIR systems, Colour 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 colour content inside an image segment, and statistically, it gives the distribution of the number of pixels in an image representing a particular colour and denotes the joint probability of the intensities of the three colour channels (R=Red, G=Green, and B=Blue channels). Quantization in terms of CHs indicates to the process of reducing the number of bins by collect the colours that are very similar to each other in the same bin. Colour range is between 0 and 255 in each of the colour bands, in this work, we consider 4 shades wide bins. Therefore the colour histograms are 64-bins histograms

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(Chatzichristofis, S.A., and Boutalis, Y.S. 2011; Krishnamoorthi, R. 2012; Gupta, V., and Ramawat, A. 2012). Formally, a CH for a given image is defined as a vector:

$$\mathbf{CH}(N)= \{\mathbf{H(0), H(1),\ldots H(j),\ldots H(M)}\} \quad (1)$$

Where

CH is a colour histogram, the colour in CH is declared by j, the number of pixels of colour j in image N is represented by H(j), and M is the number of bins used in CH. In order to compare between CH of different size, CH should be normalized using equation (2) (Murala, S., *et al*, RP. 2009):

$$\mathbf{CH' = CH} / \sum \mathbf{p} \quad (2)$$

Where, p is the pixel in the image.

Colour Layout Descriptor (CLD):

Colour Layout Descriptor (CLD) descriptor is used widely in image retrieval system to represent image colour, and it has been designed to efficiently represent the spatial distribution of colours. CLD is obtained by applying the Discrete Cosine Transform (DCT) transformation on colors 2-dimension matrix of local representative colours in YCbCr colour space. CLD extraction process involve four stages; *firstly*, partition the image into (8 x 8) 64 blocks, to assurance the invariance to scale or resolution. *Secondly*, from each block, any method to represent the colour can be applied, but due to the simplicity and suffice to descript the colour accuracy, the average of the colour pixels is computed, then convert RGB color space to YCbCr. In the *third* stage, the luminance (Y) and the blue chrominance (Cb) and red chrominance (Cr) are transformed by 8x8 DCT, therefore, we obtained three sets of 64 DCT coefficients. Fourthly, perform the zigzag scanning 3 [8x8] matrix of 64 coefficients (DCTY, DCTCb, DCTCr) in order to group the low frequency coefficients of these matrix, the output of this stage are three zigzag scanned matrix (DY, DCb, DCr) which represent the CLD descriptor of the input image (Safinaz Mustapha and Hamid. A. Jalab, 2012). Finally, to evaluate the similarity between CLD of query and database images can be performance using equation (3) as:

$$\boldsymbol{D} = \sqrt{\sum_i \boldsymbol{W_{yi}}(\boldsymbol{DY_i} - \boldsymbol{DY'_i})^2} + \sqrt{\sum_i \boldsymbol{W_{bi}}(\boldsymbol{DCb_i} - \boldsymbol{Db'_i})^2} + \sqrt{\sum_i \boldsymbol{W_{ri}}(\boldsymbol{DCr_i} - \boldsymbol{DCr'_i})^2} \quad (3)$$

Where Yb, Cb_i, and Cr_i denote the ith coefficients of Y, Cb, Cr color component, and w_{1i}, w_{2i}, and w_{3i} are the weighting values for the ith coefficient, respectively. We can weighting the coefficients (w) in order to adjust the performance of the matching process. These weights let us give to some components of the descriptor more importance than others. The retrieve image is the same of query image if D is equal to zero and two images are similar if D is near to 0.

Texture feature:

Texture feature, has been one of the robust low-level feature and the most important for image recognition and retrieval because it is provide a good information about the relationship between the pixels in a local area (region) or in a whole image (Jian Yang and Jingfeng Guo, 2011). Methods related to texture features can be divided into two approaches; statistical and frequency (filtering) approaches. Statistics or numeric quantities that represent a texture can be computed from the colours or gray tones alone. This approach is less intuitive, easier and efficient to compute, and it is commonly used for segmentation, classification, and image retrieval. Gray Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP) are examples among the statistical approach, While frequency approach represent an image texture as a set of primitive texels in some repeated or regular pattern (Neetesh, G., and Dey, PK., 2011,Alice Porebski, *et al*, 2008). Gabor filter, wavelet transform, etc. are examples of frequency approach. In this paper, the statistical approach including GLCM and LBP are extracted to represent the texture feature in our proposed CFBIR system.

Gray-Level Co-occurrence Matrix (GLCM) Features:

Gray Level Co-Occurrence Matrix (GLCM) was introduced by (R.M. Haralick, *et al*, 1973). GLCM has shown to be a general method of extracting second order statistical texture feature from an image. It is based on studies of pixel intensity distribution statistically. Also, it express the probabilities $P(i, j \mid d,\theta)$ with which two pixels having relative polar coordinates (d,θ) appear with intensities i, j. Flowing all factors that should be determined in order to extract GLCM feature (P. Mohanaiah, *et al*, 2013, Thakare, *et al*, 2014):

- The angle (θ) which represent the spatial relationship and it is limited to (0^o, 45^o, 90^o, and 135^o),
- Specify displacement vector d=(dx, dy) between the interest pixel and its neighbour pixel over the image, *d* could take the value of (1,2,3,…n).
- The number of gray levels (G), a typical value of G is 4, 8, 16 or 32.

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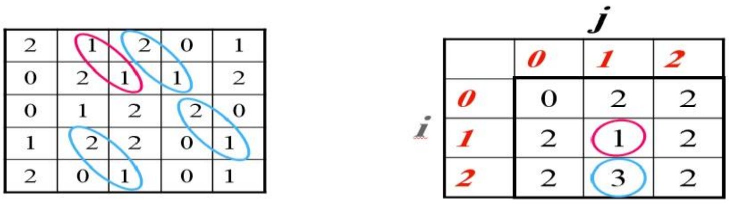
These factors mean that the gray scale has to be compressed into a much smaller set of values and careful choice of specific sample (d, θ) values must be made. The output is GLCM in 2-Dim square matrix form, the number of row (i) and column (j) which represent the size of GLCM matrix is depend on the number of G (P.G.Reddy, 2010). We can get multiple number of GLCM matrices depending on different values of d and θ. The information obtained from single GLCM by using one direction might not be sufficient to describe the image texture feature, therefore, in this paper, numerous experiments were carried out using best angle selection experimentally (45º together with 135º), displacement d=1, and G = 8 to compute multiple GLCMs for a single input image. The GLCM feature is formed by adding GLCM matrix together, the result is (8-by-8) matrix, i.e. 64-dimension. Fig (7) show an example of creating GLCM Matrix. In this example, d = (1,1) which mean one pixel right one pixel down, p(I,j) indicates how many times value i co-occurs with value j displaced by d. There are 16 pairs, so we should normalized it by 16 (divide each element in the matrix by 16).

Local Binary Pattern (LBP):

The standard Local Binary Pattern (LBP) operator is defined as a gray scale invariant texture measure that be derived from a general texture definition in a local-neighborhood. LBP operator was first produced and described in (T. Ojala, *et al*, 1996). Basically, LBP is a good descriptor that gets small texture details, and it has since been found to be an important and a powerful feature of texture classification of gray scale image. An Important properties for LBP that is invariant to any monotonic gray level change and computational simplicity. In a simple form, LBP feature vector, is extracted by using the following algorithm:



a b

Fig. 3: a: Simple image with gray level values 0,1,2; b: GLCM Matrix.

1. Divide the image into several small regions (cells) (e.g. 3×3 neighbors).
2. The operator assign a label to every pixel of an image using the center pixel as a threshold and compares the threshold with all the neighbors' pixels (on its left-top, left-middle, left-bottom, right-top, etc.). Follow the pixels along a circle, i.e. clockwise.
3. When the center pixel's value is greater than the neighbor's value, the gray-level values labeled by "1", otherwise, labeled by "0". This gives an 8-digit binary number. This gives an 8-digit binary number, then converted to decimal number.
4. Compute the histogram, over the cell, of the frequency of each "number" occurring (i.e., each combination of which pixels are smaller and which are greater than the center).
5. Normalize the histogram (optionally).
6. Concatenate histograms of all cells. This gives the LBP feature vector for the window.

Figure (4) illustrate an example of computing LBP in a 3x3 neighborhood:

Example

6	**5**	**2**
7	**6**	**1**
9	**8**	**7**

Thresholded

1	**0**	**0**
1		**0**
1	**1**	**1**

Weights

1	**2**	**4**
128		**8**
64	**32**	**16**

Pattern = 11110001; LBP = 1 + 16 +32 + 64 + 128 = 241

Fig. 4: The principle of LBP feature extraction.

Shape feature:

Shape is one of an important and powerful image features that used in CBIR system and defined as the characteristics that capture salient geometric details in the image (S.Z. Li, 1999). Generally, shape is categorized into two classes: (contour and region)-based shape. Boundary-based method, where it uses only the external borders of the shape by describing the region using its external properties which mean the pixels located over the object boundary; while the region-based method consider on the entire area of the shape (object) by describing the region using its internal properties; which mean the pixels located inside that region (Marinette Bouet, et.al,1999). The most commonly techniques are used for these groups are Canny Edge Detection (CED)

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and Hu's seven invariant moments. The main idea of CED descriptor is to use boundary-based moment as shape feature and the main idea of Hu's invariant moments is to use region-based moments which are invariant to transformations, as the shape feature descriptors.

Canny Edge Detection (CED):

The Canny Edge Detection (CED) operator was produce to be an optimum edge detector. It produce an output image showing the position of an input a gray scale image, and produces as output an image showing the positions of tracked intensity discontinuities. CED feature developed by John Canny in 1986 (J.F. Canny, 1986) to find edges in an image of many applications like face detection, image retrieval, security and much more. The algorithm of CED include the following steps (E. R. DAVIES, 2012, Raman Maini and Dr. Himanshu Aggarwal, 2009):

1. Image smoothing with a Gaussian filter. Compute the gradient magnitude and orientation using finite-difference approximations for the partial derivatives
2. Compute the gradient magnitude and direction (vertically, horizontally, or diagonally), so the edge detector operator returns the first derivative in horizontal and vertical direction.
3. From the given values of image gradient, the direction of edge is calculated by comparing the gradient value with its local maxima. This step is also called as non-maximum suppression because it gives a wide range of edges including thin edges. The edge direction is compute by comparing the gradient value with its local.
4. Once the gradient values have been computed, thresholding is performed to detect and link edges. The total number of edge points depends on the value of threshold. Large the value of threshold produce small number of edges. Small the value of threshold produce large number of edges.
5. Edge thinning is performed to remove the false edges that are shown in image. It removes all the unwanted edge pixels.

Hu's Seven Invariant Moments:

Moment-based invariants are the most common region-based image invariants which have been used as pattern features in many applications. To extract the shape feature, invariant moments based on one that was proposed by Hu (H. Ming-Kuei, 1962) is presented. These moments are resulting from second and third order central moments and they are invariant under changes and translation in rotation and scale. Moment invariants have been extensively used in a variety of image applications like image pattern recognition, image registration, and image retrieval and have been proved to be the adequate measures due to its invariant features on image rotation, scaling, and translation. (Huang, Z. , and Leng, J. 2010, CH Teh, and RT Chin, 1988, Qing Chenl, *et al*, 2004). Often the values of some moments are relatively small or zero, therefore sometimes the values of momenta are normalized between 0 and 1.

$$I_1 = \eta_{20} + \eta_{02}$$
$$I_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2$$
$$I_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2$$
$$I_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2$$
$$I_5 = (\eta_{30}-3\eta_{12})(\eta_{30}+\eta_{12})[(\eta_{30}+\eta_{12})^2-3(\eta_{21}+\eta_{03})^2]+(3\eta_{21}-\eta_{03})(\eta_{21}+\eta_{03})[3(\eta_{30}+\eta_{12})^2-(\eta_{21}+\eta_{03})^2]$$
$$I_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})$$
$$I_7 = (3\eta_{21}-\eta_{03})(\eta_{30}+\eta_{12})[(\eta_{30}+\eta_{12})^2-3(\eta_{21}+\eta_{03})^2]-(\eta_{30}-3\eta_{12})(\eta_{21}+\eta_{03})[3(\eta_{30}+\eta_{12})^2-(\eta_{21}+\eta_{03})^2].$$

The seven moments are used as a shape feature with 7-dimensional FV.

On-Line Stage:

One of the problems that sometimes encounter the museum staff, is about the search and finds the art work or specific painting in their image database especially when the query image submitted is unknown representation of the original image or unclear in the resolution, etc. So, the following six different transformations will be applied to each original image and used them as query for testing purpose:

1. Three image rotations with three degrees (90, 180, and 270).
2. Noise addition; pepper and salt noise is adding to the query image which mean that bright pixels over in the dark region and also dark pixel over in the bright region.
3. Cropping by remove the pixels only from the image periphery;
4. Image Pyramid.

Then, the same procedures used for database images will be applied for each query image to obtain the Query Feature Vector (QFV). Figure (5) show the block diagram of on-line stage.

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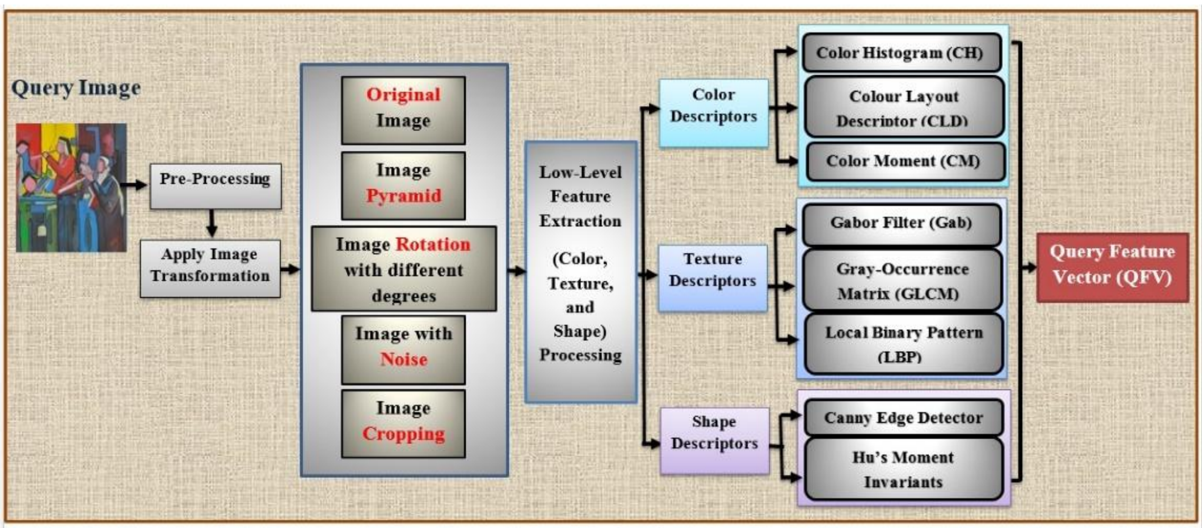

Fig. 5: Block diagram of on-line stage.

Descriptors Selection Stage:

To perform the image retrieving based individual image feature of proposed CFBIR system, 700 test images have been used as query images including 100 original museum image and 600 transformations images. The similarities between the query image and database images are calculated using L2 metric which known as Euclidean distance which examining by computed the root of the squared difference between the QFV and DFVs. The distance values are stored and sorting in ascending order, the zero or lowest distance value indicate to the most similar between the query image and database images. Basically, the key to perform an efficient retrieval system is to choose the accurate features that represent the image as unique as strong as possible. So To evaluate all feature descriptors for each type of query image, we compute the percentage of successful retrieval, which mean that the original museum image is retrieve as the first image in the retrieval results. Table (1) listed the average accuracies of retrieval results for all query types and descriptor and shows the comparison results obtained by image retrieval based individual colour feature (CH and CLD), texture feature (GLCM and LBP), and shape feature (CED and Hu's moments).

Table 1: Average of success retrieval rate of (colour, texture and shape) Descriptors for each query type..

	Success Retrieval Rate					
	Colour Descriptors		Texture Descriptors		Shape Descriptors	
Transformation of Query Image	CM	CH	LBP	GLCM 45°+135°	CED	Hu's 7 moments
Original Image	100	100	100	100	100	100
Image Cropping	80	100	39	76	24	67
Image Pyramid	97	100	17	29	100	95
Image with Salt & Pepper Noise	60	98	5	92	45	66
Image Rotate with 90 Degree	99	100	97	100	7	100
Image Rotate with 270 Degree	97	100	93	100	9	100
Image Rotate with180 Degree	98	100	94	100	16	100
The Average	90.14	99.71	64.57	85.29	43	89.71

The results shows the descriptors with high success rate represented by CH, GLCM, and Hu's moment as colour, texture, and shape descriptors respectively, and consider these descriptors as most appropriate descriptors, therefore, in the next sections, combined these features using early fusion technique and proposed features fusion technique, then compare between all the results obtained from different feature fusion techniques is presented. The diagram of retrieval and descriptors selection stage is show in figure (6).

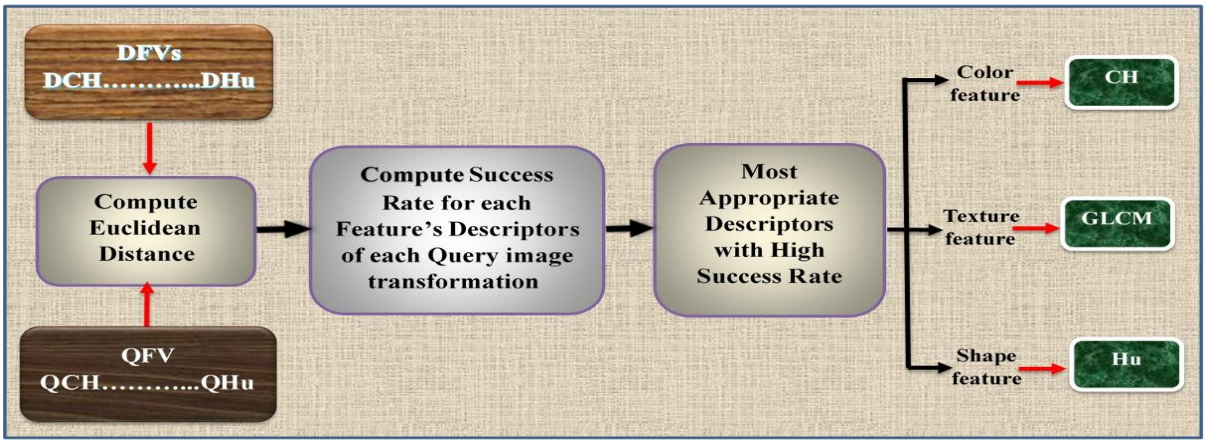

Fig. 6: Block diagram of descriptors selection stage.

Image Retrieve Based Fusion Features:

To increase the accuracy of image retrieval system, a new trend is the fusion of visual features. Recently, fusion of descriptors has become a trend for improving the performance in image and video retrieval tasks (Andrade, F., *et al*, 2012). In this section we present; firstly, introduction to fusion strategies and related work, secondly, using one of the general fusion technique named *Early fusion*technique to perform a comparative study of the possible features combination, thirdly, proposed new feature fusion technique using XOR function to avoid the drawback of EFFT, and lastly, a comparison between the results of early and proposed feature fusion technique is presented.

Fusion Strategies and Related Work:

Fusion is defined as an important aspects of an intelligent system and includes the combination of data/information together from multiple resources to form useful information. Fused data/information are more enriched in information than whose bring from a single source, else the data/information would not be fused. So, the fusing data from multiple sources is considered as intelligent process. By using the fusion techniques we will attempt to increase the accuracy of the data. Mainly, there are three types of fusion strategies (Gee Wah Ng. Intelligent Systems, 2003; Snoek, C.G.M., *et al*, 2005, Mangai, *et al*, 2010):

1. Data/information fusion (low-level fusion),
2. Decision fusion (high-level fusion), also named Late fusion, and
3. Feature fusion (intermediate-level fusion), also named Early fusion.

In data fusion combines several sources of raw data to produce new raw data that is expected to be more informative and synthetic than the inputs. Decision fusion (late fusion) merges the outputs of all features matching together to obtain the final output. Feature fusion (Early fusion) deal with the combination several incoming features into one fused vector which is then used in a traditional classifier and also deal with features selection in order to remove one of the features who have similar or nearly similar distribution because one of them is redundant (Tan, X., and Triggs, B. 2007, Yang, J., *et al*, 2003). Clearly from this definition, feature fusion is an advancement of information fusion and widely used in many applications such as face recognition (Mirhosseini, A.R., *et al*, T. 1998),medical image processing(Constantinidis, AS, *et al*, 2001),Remote sensing(Briem, G.J., *et al*, 2002),object recognition, speech processing and video classification and retrieval (Arevalillo-Herráez, M., *et al*, 2008). Image retrieval system (Zhang, J., and Ye, L. 2009, Zhang, J., & Ye, L. 2010). In this paper, EFFT is produce to fuse the most appropriate descriptors of colour, texture, and shape features.

Early Fusion Technique:

Early Feature Fusion indicate to combining various individual feature vectors that are got by applying many feature extraction algorithms to form a new single feature vector before matching process. Sanderson and Paliwal (C. Sanderson, and K.K. Paliwal, 2002, Spyrou, E., *et al*, 2005) have suggest two fusion methods can be used in early feature fusion:

1. A weighted average of the individual feature vectors, this method is used when the FVs are homogeneous, to form a new single feature vector.
2. Concatenate individual features to form a new single feature vector, this method is used when the FVs are nonhomogeneous and obtained by using various FE techniques.

Since the results of selection the most appropriate descriptors are nonhomogeneous, so fuse these FVs in concatenation manner to form a large single Database Feature Fusion Vectors (DFFVs) and Query Feature Fusion Vector (QFFV). Then use them later in the matching process using the Euclidean distance to calculate

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the distance values between DFFVs and QFFV in a high dimensionality space. So the similar images are displayed depend on the distance values, the zero value indicate to the same query image, smaller value indicate to the most similar image to the query image, and the higher value indicate to the un similar image to the query image. Figure (7) shows the block diagram of image retrieval using EFFT to concatenate the most appropriate feature descriptors.

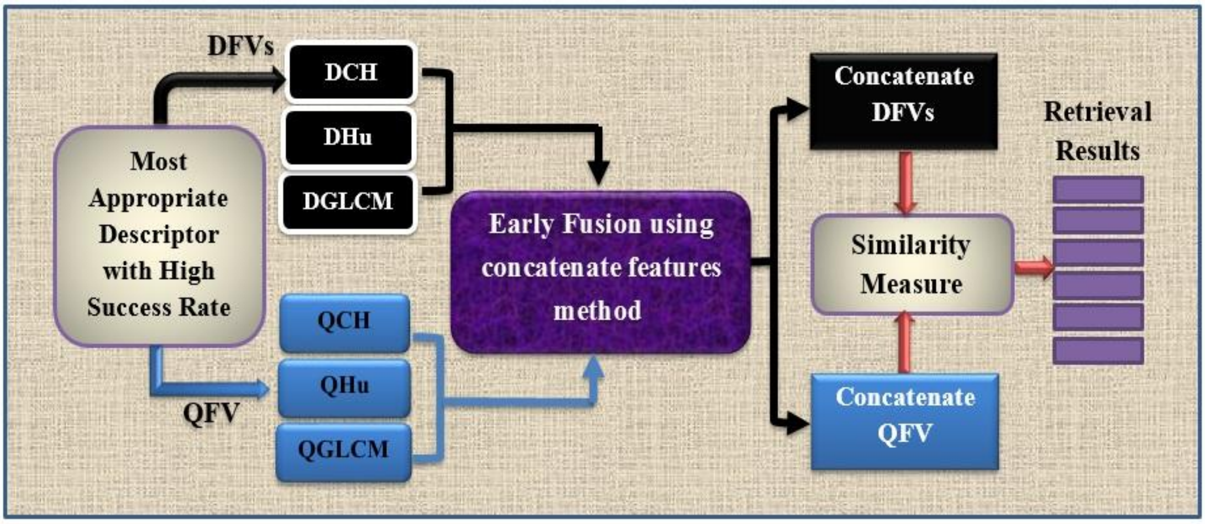

Fig. 7: Block diagram of image retrieval based Early Feature Fusion technique.

Proposed Feature Fusion Technique using XOR Function:

Although the fusion feature vectors that obtained by fuse multiple features vector using EFFT give extra knowledge and can increase the performance of image retrieval system, But at the same time, it may be yield feature vectors with hundreds or even thousands of dimensions which is lead to the so-called "dimensionality curse", consequently, it is going to be very time-consuming for retrieving similar images from a large database like museum image database. As we saw from table (1), the most appropriate descriptors that selection are CH, GLCM, and Hu's moment with 64, 64, and 7 dimension respectively. The concatenation method can lead to two problems; Firstly, the resulting feature vector may have a very large dimensionality, in our case is equal to 135 dimensions and the problem referred to as the "curse of dimensionality". The second problem is the scale effect due to the different magnitude of numerical values of the individual feature vectors. Scale effects can be addressed by re-scaling or normalizing feature vectors. A detailed study of normalization techniques can be found in (Gupta, V., and Ramawat, A. 2012). To avoid the drawbacks of using EFFT, new proposed feature fusion technique using XOR function is produce to obtain the final results in a short time as we will see that in our experiments.

XOR Fusion Algorithm:

The binary XOR (exclusive OR) operation also known as the binary XOR function has two inputs and one output. The inputs to a binary XOR operation can only be 0 or 1 and the result will be 1 if either of its input is 1 and will produce a 0 output if both of its inputs are 0 or 1. Table (2) shows the output C of combine two inputs A and B using XOR function:

Table 2: XOR Truth Table.

Input A	Input B	Output C
0	0	0
0	1	1
1	0	1
1	1	0

The proposed fusion technique using XOR function will be apply to fuse CH, GLCM and Hu's moments and the process include the following steps:

1. Normalize individual FV of CH, GLCM and Hu's moments feature.
2. Reshape the feature vector of CH, GLCM and Hu's moments feature.
3. Equal all the features vector to be equal to the largest one.
4. Convert the values of each feature vector to the binary numbers,
5. Apply the XOR function, firstly on only two vectors, let it be CH and GLCM to get one vector.

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6. Then, apply the XOR function on the vector yield from step (5) with the Hu's moment vector to get the final feature fusion vector of all database images (DFFVs).
7. Repeat the steps from 1-6 on query image to get the final feature fusion vector of query image (QFFV).
8. Compute the similarity between QFFV with DFFVs using Euclidean distance to get the distance values for each image.
9. Store the distance values and sort them in ascending order.
10. Retrieve the images with zero or smallest distance value to be the similar images.
11. Calculate the average of success retrieval that mean retrieve the original image like the query image as the first result of all feature descriptors for each type of query.

Table (3) show the results of combine CH, GLCM, and Hu' moments using EFFT and proposed feature fusion using XOR function.

Table 3: Show the comparison between EFFT and proposed Feature Fusion Technique sing XOR function.

Translations of Query Image	Early Feature Fusion	Proposed XOR Method
	(CH + Hu's 7 Moments) + GLCM	(CH + Hu's 7 Moments) + GLCM
Original Image	100	100
Image Rotate with 90 Degree	96	100
Image Rotate with 270 Degree	96	100
Image Rotate with180 Degree	100	100
Image Cropping	91	84
Image with Salt & Pepper Noise	50	74
Image Pyramid	100	95
Average	90.429	93.286

Effectiveness of proposed Feature Fusion Technique:

Our proposed feature fusion technique is compared with EFFT to experimentally illustrate the efficiency of this fusion;

Our proposed technique yields significantly better retrieval accuracy. There is a 93.286% improvement in the overall retrieval accuracy, which indicates that the combine features using XOR function dramatically increase the accuracy of retrieval performance and it is more effective than EFFT.

RESULTS AND DISCUSSION

The main objectives of this paper is to design and implement image retrieval system for Iraqi National Museum of Modern Art. So the real database is created by selecting 100 original images randomly from museum image collections. In order to achieve a good performance, it should be select the appropriate image features which represent the main component of any image retrieval system. In this paper, different colour, texture, and shape methods were applied. Table (1) shows us the results of the average of success retrieval rate; CH (99.71%), GLCM (85.29%), and Hu's moments (89.71%) which represent the most a proper colour, texture, and shape features descriptors respectively among another descriptors. Since we cannot rely on a single feature in the image retrieval because it cannot represent the images as much as possible, so fuse these features (CH, GLCM, and HU's moments) to increase the accuracy of system's performance has been used. This process was achieved firstly, using EFFT and the results proved the increasing in the retrieval success rate (90.422%) comparing with the results based individual feature as show in table (3). One of the main problems that occur by using EFFT, it suffer from the so-called "curse of the dimensionality" that occur due to concatenate the features vector together. Thus, the length of the fusion vector is equal to the sum of the dimensions of Features vectors. In this paper, the features fusion vector is equal to summation of CH (64), with GLCM (64), and with Hu's moment (7), totally is quale to (135) dimension. To avoid this problem, in this paper, new feature fusion method using XOR function is proposed. IN this method, the length of features fusion vector is equal to longest vector among all features and in our case it is equal to only (64) dimensions (the length of CH, or GLCM) feature, which has had the greatest effect of improving the performance of image retrieval and reduce the image retrieval time. The success rate of retrieval results of proposed fusion technique was increased to (93.286%) comparing with the result of EFFT (90.422%).

Conclusion:

An effective CBIR system requires the accuracy in the image feature selection to efficiently use most of the data from the images. In this paper, the study has been done on six low level features extraction methods (colour, texture, and shape) to comparisons between the retrieval accuracy of each method on museum images. The experiment was performed on 100 original museum images from Iraqi National Museum of Modern Art collection. Six transformations (image rotation in three direction, image cropping, image nosing, and image pyramid) was applied on each original image to obtain 700 images using as query image to test the performance of proposed CFBIR system by computing the average of retrieval success rate. Then, we selected the feature descriptors with the highest average which represent the highest accuracy among different methods. Reported results show that the best colour extraction method is Colour Histogram (CH) descriptor; for texture method Gray Level Co-occurce Matrix (GLCM) descriptor; and for shape is Hu's seven variant moments GLH) descriptor. These descriptors then combined to increase the performance accuracy using EFFT. For the combination of these descriptors gives the excellent result (90.422%) comparing with the individual descriptor. To drawback the ' curse of dimensionality' resulting from using EFFT, new feature fusion technique using XOR function is proposed and the results were promising, as it increased the retrieval performance to become (93.286%). This fusion technique can be used in museum applications to provide a dependable image retrieval system.

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