Image Retrieval Based on Chain Code Algorithm Using Color and Texture Features

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Abstract--- *The rapid growth of image retrieval has provided an efficient Content-Based Image Retrieval (CBIR) system to retrieve image accurately. In this paper, a precise retrieval result by exploiting color, texture and shape features is proposed. First, extract the features by color moment and (Hue, Saturation, Value (HSV)) color space as a color feature, and then get the co-occurrence matrix as well as Discrete Wavelet Transform (DWT) for a texture feature. Chain codes algorithm, specifically chain code histogram, is then applied to obtain the codes of the shape feature. Second, collect all these features and store it in the database, where each record represents one image of the dataset. Similarity process is executed to find the images that are more similar to the query image, retrieved images ranked. The dataset applied in this study is WANG that includes 10 classes with each class containing 100 images. Experimental results have revealed that the proposed method outperformed the previous studies with an average of 0.824 in term of precision.*

Keywords--- Chain codes algorithm, Feature extraction, (Hue, Saturation, Value), Image Retrieval and RGB.

الخلاصة : *ادت سرعة تنامي نظم استرجاع الصور الى ضرورة توفير نظام استرجاع صور دقيق. في هذا البحث دقة نتائج الاسترجاع تمت بواسطة استغلال خصائص اللون ونسيج الصور وخصائص الشكل. في البداية تم استخراج خصائص اللون المتمثلة بعزم قوة اللون (color moment) وفضاء اللون (HSV)، بعدها الحصول على خصائص نسيج الصورة عن طريق مصفوفة التوزيع (co-occurrence matrix) وكذلك تم تطبيق دالة التحويل الموجة (wavelet transform) يتبعها تطبيق خوارزمية ترميز السلسلة تحديدا المدرج التكراري لترميز السلسلة (chain code histogram) وذلك للحصول على خصائص الشكل. ثانيا، تجميع كل هذه الخصائص وخزنها في قاعدة بيانات حيث كل سجل يمثل معلومات لصورة واحدة. واخيرا تم تطبيق عملية تشابه الخواص لايجاد الصور الاكثر تشابها للاستعلام المدخل للنظام وترتيب الصور المسترجعة حسب الاكثر تشابها.تم تطبيق النظام على مجموعة من الصور القياسية المستخدمة في جميع بحوث استرجاع الصور (Wang) حيث يحتوي على ١٠ اصناف من الصور وكل صنف يضم ١٠٠ صورة. النتائج التجريبية تكشف ان الطريقة المقترحة تفوقت على نتائج الدراسات السابقة من ناحية دقت الاسترجاع.*

I. Introduction

Typically, image retrieval has become one of the common fields in information retrieval systems. Therefore, the need for the development of image retrieval methods has become interesting issue. There are many ways to retrieve images depending on the searching process, where the search process is done by finding one or more keywords described by the user as a query image to find similar images in the database. However, sometimes a suitable keyword to express the query image cannot be found. Basically, a successful (CBIR) system needs three main steps: (1) low-level image feature extraction, (2) similarity measures, and (3) semantic gap reduction.

One of the researchers is Xinjung [1]. proposed information retrieval method by organizing and sorting the information depending on a certain way where the user's requests were focused on interrelated information. At that time, the main issue in text-based information retrieval was finding a relation between descriptions of the title in addition several other bits of information and storage path of the image . However, some drawbacks of the text-based image retrieval appeared when the capacity of the database is increased: 1- there is no system to note all images in the database. 2- The precision result of the retrieval process by image annotation may generate inaccurate results.

Global features like color and texture are normally implemented to distinguish content-base image retrieval. The nodes is that by using these features, not all details of the image can be obtained where the images have several properties as [2]. In order to get acceptable information, 2D discrete wavelet transform is proposed by combining the two high sub-band frequencies and making the considerable points with edge that selects the high coefficient value according to the threshold.

Feature selection is a challenging process in CBIR systems [3] as. Most of the previous studies used color, texture, shape and space [4, 5]. Normally, Research focused on high-level semantic features of images. Additionally, integration of different features has been used in recent years. Color features are used because of easier extraction, are more widely utilized visual features in comparison with shape and texture information. Typically, characterization of color composition is performed by the method of color histograms as proposed by Swain and Ballard [6].

Normally, color histograms are sparse and sensitive to noise while cumulated color histograms, as proposed by Stricker and Orengo [7], proved better than color histograms. Since, color histograms do not incorporate spatial color distribution; their ability to discriminate is limited. On the other hand, moment based color distribution features can be more robustly matched than color histograms. Color moments have delivered successful performance in image retrieval systems.

In addition, utilization of first three-color moments in characterization of one dimensional color distribution is faster and robust than histogram method [7] Texture describes uniformity, coarseness and smoothness of the object in an image. The texture similarity can be measured by numerous techniques, most of which compare values of second-order statistics performed on query and stored images as in [8]. These techniques measure the degree of contrast, regularity, coarseness, directionality [9, 10]; periodicity and randomness [11]. Wavelet illustration tells about image variations at various scales. Discrete wavelet transform (DWT) represents the sum of wavelet functions of an image per different locations and measures [12]. Local features of an image are normally utilized for capturing specific portions of an image.

Additionally, Chain code is a shape representation that represents boundaries by sequences of connected line segments of specific length and direction. It is based on 4- or 8-connectivity of segments [13,14] where, the direction of each line segment is coded by following the numbering scheme depicted in Fig.1. Chain codes based on this scheme are known as Freeman chain codes [15].

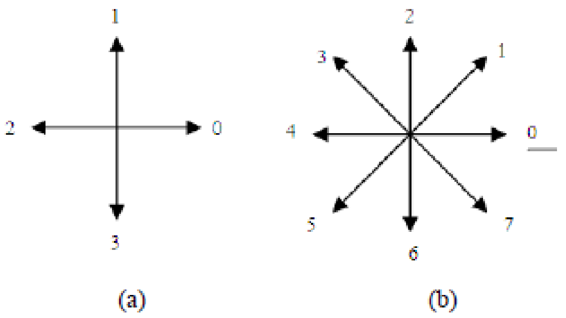

Figure 1- Direction numbers for (a) 4-directional chain codes, (b) 8-directional chain code

In this Paper, the extracted features are color histogram; color moments, HSV, co-occurrence matrix, DWT 2D discrete wavelet transform performed in combination with Haar base function. It combines two high sub-band frequencies to form prominent points and edges; significant point is then estimated by setting high value as the threshold. Furthermore, chain code algorithm is applied by describing the images through chain code algorithm where, chain code histogram counts each direction of each image and then combines these images with the previous features in a database to find the images are most similar to the query.

II. FEATURE SELECTION

Feature selection is crucial since not all features are useful in image retrieval systems. Some features may interfere and decrease the success rate of retrieval system. The purpose of feature selection is to choose the best ones among a large set of features to maximize the accuracy and simplicity of the procedure [16].

A. COLOR MOMENTS

Three color moments are always required for describing features of an image. The first moment uses mean second variance computation while the third moment utilizes skewness of the image. These have shown promising performance in color distribution of an image [17]. Here, mean gives a general estimate of the image brightness. The brighter the image is, the higher is the mean value it possesses and vice versa. By definition, mean can be represented mathematically by equation (1) [18].

$$\mu i = \frac{1}{N}\sum_{j=1}^{N} f_{ij} \qquad (1)$$

where, f_{ij} represents value of the color components with descriptors i and j mentioning about color component and image pixel respectively. Also, N represents pixel number in the image.

Variance is a measure of the local variation in pixel and intensity of an image. Square root of the variance is termed as standard deviation (STD) that estimates contrast of an image and range of the data. The higher the contrast in an image, the higher the STD value it holds and vice versa. Variance and standard deviation can be represented mathematically by equations (2) and (3), respectively [17].

$$\sigma_i^2 = \frac{1}{N}\sum_{j=1}^{N}\left(f_{ij} - \mu_i\right)^2 \qquad (2)$$

$$\sigma_i = \left(\frac{1}{N}\sum_{j=1}^{N}\left(f_{ij} - \mu_i\right)^2\right)^{1/2} \qquad (3)$$

where f_{ij}, j, N and μ_i are value of the color component, pixel number, number of feature over all databases, mean and the color, respectively. Skewness depicts symmetry around the mean value and can mathematically be represented by equation (4).

$$s_i = \left(\frac{1}{N}\sum_{j=1}^{N}\left(f_{ij} - \mu_i\right)^3\right)^{1/3} \qquad (4)$$

Color moment is therefore a decent representative for comparison of color features. Also, it is used at the initial stage to narrow down the search space before implementation of the proposed method of image retrieval [17].

B. (HUE, SATURATION, VALUE (HSV)) COLORS

HSV, also known as HSB (Hue, Saturation, and Brightness) color space originates from intuitive appeal of the artist's tint, shade and tone. HSV color space is cylindrical but has a common representation of a cone or hexacone as displayed in Fig.2. Saturation 'S' and Value 'V' are found in the range [0, 1] while Hue 'H' is given by angles, where 0° indicates red, 60° indicates yellow and so on [19]. In this study, the values of H, S and V are used to extract the features of the

HSV color space. For example if h=7, s=2, v=1, then put 1 to the matrix 8x2x2 in position 7, 2, 1)

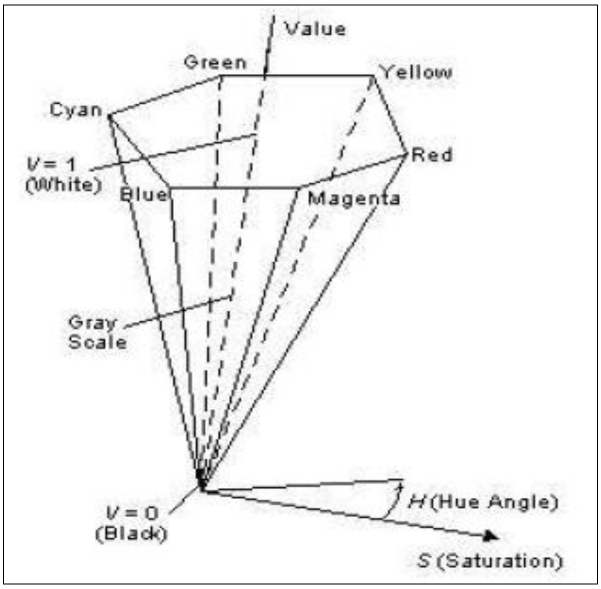

Figure 2- HSV color space. [19]

C. (GICM)TEXTURE FEATURES

In statistical methods the interactions of pixels within the spatial gray level dependency (SGLD) matrix are modeled by second-order statistics [20]. The tabulation of co-occurrence matrix mentions alteration frequency of pixel-value combinations in the image. It is too large to extract useful features of the image. The extracted features of an image are termed Haralick features that cover correlation, homogeneity, contrast and energy [16]. Co-occurrence matrix C (i, j) can be used to calculate the co-occurrence of gray pixels with i and j values at polar co-ordinates of (d, θ) [18]. Practically, θ can assume the values of 0°, 45°, 90°, 135°, 180°, 225°, 270° or 315°. In this study, the 0° is used which considers the default angle. The co-occurrence matrix C (i, j) is described by equation (5).

$$C_{\theta * d}(i,j) = \# \begin{cases} 1 & \text{if } I(x_1, y_1) = i \text{, and } I(x_1 + d\cos\theta, d\sin\theta) = j \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

Where, i and j are gray-level values and d is the difference between them. Also, # mentions the number of elements in the set. The number of possible gray-levels in the image are i, j = 0.255 and the dimension of co-occurrence matrix C (i, j) is $M_x N$ [16] [18] [21].

Homogeneity, uniformity, angular second moments are consistency measures of an image and the energy can be referred to these quantities. Value of the energy is smaller when the difference between gray-level values is small; conversely, if matrix elements are irregular the energy value elevates. Mathematical description of energy is given by equation (6).

$$\text{Energy} = \sum_i \sum_j c_{\theta,d}^2(i,j) \quad (6)$$

where i, j are gray values of an image, while Θ and *d* are angle and distance between them.

Contrast can also be termed as inertia. It is measure of the difference moment of the matrix that has high value for high local variation in the image. Mathematically, contrast can be described by equation (8).

$$\text{Contrast} = \sum_i \sum_j (i-j)^2 \, c_{\theta,d}(i,j) \quad (8)$$

Inverse difference moment is local homogeneity of the image and hence is the inverse of the contrast. The uncertainty in matrix elements represents similar gray levels next to each other and results in high value of the function, as given by equation (9).

$$\text{Inverse Difference Moment} = \sum_i \sum_j \frac{c_{\theta,d}(i,j)}{|i-j|^2}, i \neq j \quad (9)$$

Correlation gives an estimate of the linear dependency of gray levels in the matrix; however, its high or low value does not provide any immediate information about the image. Mathematical description of correlation is given by equation (10).

$$(10) \quad \text{Correlation} = \frac{\sum_i \sum_j (i\,j) c(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}$$

Where, μ_x and μ_y are means and σ_x and σ_y are standard deviations. These are defined by following equations 11, 12, 13 and 14:

$$\mu_x = \sum_i i \sum_j c(i,j) \quad (11)$$

$$\mu_y = \sum_j j \sum_i c(i,j) \quad (12)$$

$$\sigma_x = \sum_i (i-\mu_x)^2 \sum_j c(i,j) \quad (13)$$

$$\sigma_y = \sum_j (j-\mu_y)^2 \sum_j c(i,j) \quad (14)$$

D. WAVELET TRANSFORMATION AND WAVELET MOMENTS

Wavelet illustration describes the variations in image at various scales, while, discrete wavelet transform is the sum of wavelet functions of an image per different locations and measures [22]. Fig.3 shows new images prepared from a novel NxN pixel images for each level of decomposed image.

Size of the new images reduces to one fourth of the novel image i.e., N/2xN/2. New images are filtered and applied to the novel image on horizontal and vertical guidelines e.g., the LH image is obtained by applying the low-pass filter in horizontal and high-pass filter in vertical trend, respectively. Four images are therefore produced for each decomposition level (LL, LH, HL and HH). The LL image is reduced version of novel as retained details, while, LH and HL images are exclusive horizontal and vertical edge features, respectively. On the other hand, HH images carry high-frequency noisy but trivial information. Therefore an LL image makes the next level of decomposition by wavelet [21] [22].

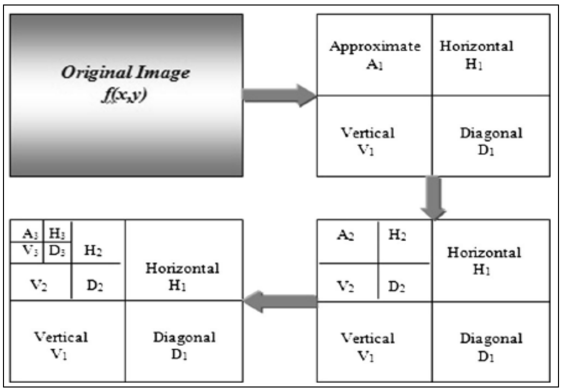

Figure 3-. Three-level wavelet decomposition of an N×N pixel image

First and second-order moments i.e., mean and variance computations are described previous by equations 1 and 2 respectively. Whereas, the input f (x, y) is in four levels that is mentioned as output of the wavelet transform.

E. CHAIN CODES

Chain code is a common algorithm used to represent the shape of the image. It was initially introduced by Freeman and is known Freeman Chain Code (FCC). This algorithm has two types of connections, 4-connected and 8-connected path [13, 14]. Moreover, the angle between each direction is 45°, where it gives accurate description of the image more 4-connected Fig. 4 (a) shows 4-connected and Fig. 4 (b) shows 8-connected FCC. In this study 8- connected method is applied to symbolize the image. At the beginning, the image is converted to borders by using some methods of edges detection such as canny detection, and then chain code algorithm is applied by tracing the direction of the border from one pixel to another [14].

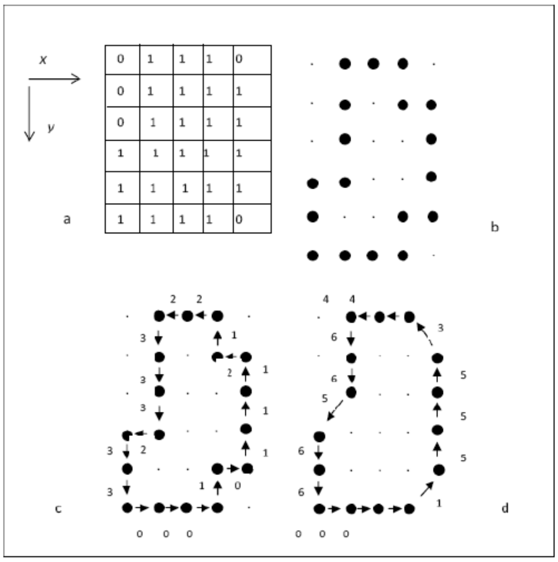

Figure 4: (a & b) A 4-connected object and its boundary; (c & d) Obtaining the chain code from the object in (a b) with (c) for 4-connected and (d) for 8-connected

III. PROPOSED METHOD

In the proposed method, there are three main steps to extract the features. First, extract the color features of the images by using color moments and HSV color space. The features of the color moments include computing mean and STD of all images in the dataset.

Moreover, the features of the HSV color and color moments are computed and stored in vector. Second, the texture features are extracted which include co-occurrence matrix and DWT that are also computed and stored in another vector. Finally, the shape features are extracted by applying chain codes algorithm. The image is converted to the gray scale image and then transformed to the binary image, by using canny detection of the border of the specified image; Fig. 5 depicts the border of the images after applying canny detection. In addition, the chain codes are implemented where; the values that are extracted from the images by applying chain code are counted as the concept of the histogram. In other words, each code and each movement of chain codes is counted and put in counters, where 64 counters are used to indicate the figure of the image. These values of the counters are then stored in an array which is called chain code histogram. Fig 6 shows chain code and its histogram. Furthermore, all the features are stored in one vector, and there are 109 extracted features where all the images have the same number of features. Table 1 shows the details of the features numbers.

Table1- details features number

Feature name		Number of features
Colors	HSV	32
	Color moments	6
Texture	Co-occurrence matrix	5
	DWT	2
Shape	chain codes	64
Total features		109

a

b

Figure 5- specified the border of the image, where (a) original image and (b) canny detection result

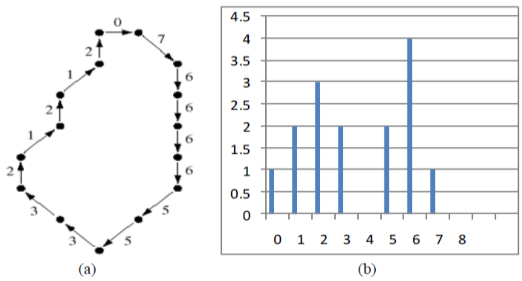

Figure 6- (a) Freeman Chain code: 076666553321212 (b) Chain code Histogram

The proposed CBIR algorithm

The following steps depict the process of the proposed algorithm that is used to retrieve images that are more similar to the query image:

Input: query color image and dataset of images.

Output: *n* images retrieved similar to the query image Methods.

Step 1: Select certain image from the dataset as a query.

Step 2: Extract color (color moments and HSV color), texture (co-occurrence matrix and DWT) and shape (chain codes) features from images in the dataset during offline stage and from query image through online stage by applying previous equations.

Step 3: Create the features vector that represents the values of the features extracted in step 2, where the total number of the features is 109 for each image.

Step 4: By using Manhattan distance the similarity is calculated between the query image and the features of the images in the database to find the smallest distance. Equation 15 described the similarity formula, stores all the results of the similarity in a vector, then resorts this vector in an ascending sort manner.

Step 5: Retrieve top *n* images belonging to image most similar to query image, where in this study *n* equals10.

$$\text{similarity} = \sum_{i=1}^{n} |q_i - o_i| \qquad (15)$$

where, q_i indicates the features of the query image, o_i refers the features of the certain image in the dataset and *n* is the number of the features. The proposed method to be implemented in this study is shown in Fig. 7.

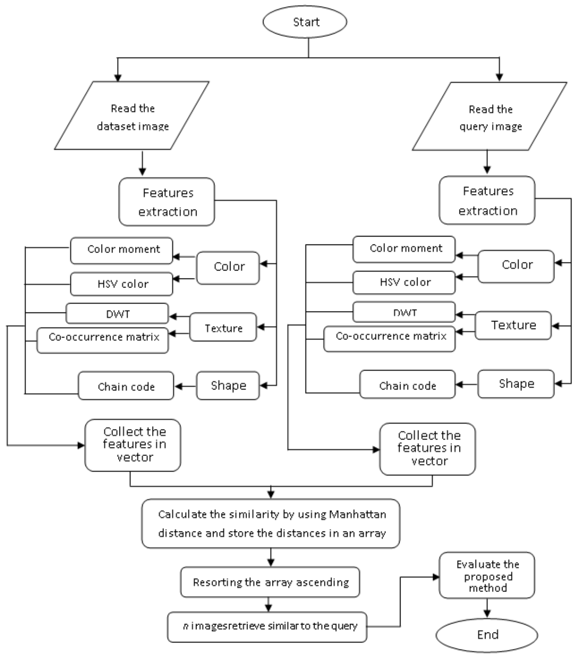

Figure 7- Proposed Flowcharts

EXPERIMENTAL RESULT

After the implementation process, the proposed method is evaluated by comparing the proposed results with previous work. The similarity between dataset and the query image is computed via the Manhattan distance to find the closest image to the query.

The dataset used in this research is WANG database that is considered standard database in image retrieval. This dataset consists of 10 classes for different types of the images and each class contains 100 images [23]. The global structures of the images in the same class are almost the same, but there are some differences in the features in the same class (for example, color). At the same time, there are some similarities of the images in the different classes (for instance, the boundaries of the buildings and the boundaries of the buses).

The evaluation process is done by computed the precision, where this function is the common measurement to check the performance of the CBIR system. The proportion of the number of relevant images to the total number of retrieved images is computed with precision [24, 25].

$$precision = \frac{Numbers\ of\ relevant\ images\ retrieved}{Total\ number\ of\ image\ retrieved} \quad (16)$$

In CBIR, when the result of the precision is one, all retrieved images are relevant. The proposed method represents a new method to retrieve the images in CBIR system. The proposed methods is implemented under Win7 with Core i5 CPU and RAM 2G, also Matlab 2010b is used to execute this method and the average of the execution time is 9.39 second.

In order to evaluate the proposed method, the results should be benchmarked with other methods. The images that tested in the proposed method are selected randomly. Table 2 displayed some samples of these images and Table 3 shows the precision average comparison between our proposed method and other methods.

Table 2- Precision comparison between proposed methods with the previous works

Query	CTDCBIRS (2011)	Afifi and Ashour (2012)	Zeyad Safaa Younus et al. (2014)	Proposed method
Africans	0.5620	0.600	0.890	0.700
Beach	0.5360	0.700	0.730	0.750
Architecture	0.6100	0.800	0.701	0.778
Busses	0.8930	0.700	0.838	0.944
Dinosaurs	0.9840	0.700	0.998	0.999
Elephants	0.5780	0.500	0.795	0.600
Flowers	0.8990	0.700	0.925	0.950
Horses	0.7800	0.500	0.871	0.875
Mountains	0.5120	0.500	0.550	0.750
Feed	0.6940	0.400	0.755	0.889

Table 3- precision average results of the proposed method VS previous studies

Method	Precision average
CTDCBIRS (2011)	0.705
Afifi and Ashour (2012)	0.61
Zeyad Safaa Younus et al. (2014)	0.805
Proposed method	0.824

Table 2 shows the comparison results of the proposed method under the terms of precision with previous works beginning with CTDCBIRS (2011) extending to Zeyad S. Y. et al. (2014). The classes of images were considers, each with 100 images. The results have displayed that the precision metric has almost minimum value in CTDCBIRS (2011) and this value increased slightly in the rest of the studies until reaching the maximum value in the proposed method. Furthermore, the proposed method showed higher results than previous studies for most classes, especially for Dinosaurs and Flowers that are close to 1.0. Table 3 depicts that the proposed method is superior to the other techniques in terms of precision, where the closer average precision result of the proposed method starts at 2% for Zeyad (2014) and ends at 21% for Afifi and Ashor (2012). Hence, the proposed method produced much better results of retrieving the images that are more similar to the query image.

However, the results of the proposed method have less precision value compared with previous study in 2 classes because the proposed method used chain code method as a shape feature. As known, the chain code method is employed to represent the boundary of the shape; therefore, this method retrieves very good results when the image contains a clear structure. In contrast, the chain code method retrieves inaccurate results when the image includes overlapping structure. For example, the chain code considers the structure of the Elephant class to be similar to the structure of the Horse class. In addition, these images contain some details like grass that makes the results inaccurate.

IV. CONCLUSION

In this Paper, the image retrieval method is presented by combining chain code algorithm with color and texture features. The histogram and moments are used as color features and co-occurrence has implemented as a texture feature. For the shape, feature the proposed method employed chain code algorithm, where chain code algorithm play a major rule obtaining accurate results because this method distinguished the border of the shape and recognized the global structure of the images. All features are collected to represent the images in the database. Wang dataset is used in this study that considers standard dataset that has been applied by many researchers in the field of CBIR system. The database includes 1000 images divided into 10 different classes. Similarity process is done by computing Euclidian distance to find the minimum values of the images of the database that are more similar to the query image and ranking the retrieval of n images. Experimental results have revealed that the proposed method has successfully outweighed the well-known in precision metric comparing with other studies. Thus, it can be deduced that the proposed method is an effective method to retrieve images that are more similar to the query, because the value of the precision metric is close to 1.0 for most classes in the dataset.

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