Compact Composite Descriptors for Content Based Image Retrieval

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Abstract: ***This paper focuses on the decrement of computational time, by reducing the size of feature extraction. Thus in this work, we have explored the Compact Composite Descriptors (CCD) approach, which enables to reduce the size of image features without affecting the visual content of the image. The proposed approach has two phases. First is to identify and extract the features, by applying Colour Layout Descriptor (CLD), Local Binary Pattern (LBP) and Fourier Descriptor (FD). The second phase is employed to compare the similarity distance between the query images with the image in database, using the Euclidean Distance. The evaluation results show that, the proposed approach has been able to address the issues mentioned earlier.***

Keywords- ***Compact Composite Descriptor, Colour layout Descriptor, Local Binary Pattern, Fourier Descriptor, Content based image retrieval.***

I. Introduction

Content based image retrieval (CBIR) provides a method to retrieve images based on their contents. Most of the earlier works are largely focused on techniques to extract useful information (e.g. the colour, texture or shape features) that represents the content of images. However, of late this extraction technology is more mature; hence researchers are becoming more concerned about assisting structures or indexes that will help to quickly retrieve the relevant images with small size of feature vectors. The key to a successful retrieval system is to choose the right features that represent the images as accurately and uniquely as possible [1]. The objective of a CBIR algorithm is to determine the concerned images that are relevant to a given query in a database. One of the most important problems in content-based image retrieval is the high dimensionality due to the large feature vectors. The aim of this paper is to decrement the computational time by reducing the size of feature extraction. Thus in this work, we have explored the Compact Composite Descriptors (CCD) approach, which enables to reduce the size of feature extraction, without affecting the visual content of the image.

II. Related Works

Hiremath [2], has managed to present satisfying result with the combination of colour, texture and shape features. The colour and texture information are computed using the co-occurrence histogram and shape information are extracted using Gradient Vector Flow (GVF). We have realized that the result shown is basically compared with other works that use one or two low level features. Thus, definitely the accuracy results are higher because, Hiremath [2] has used more low level features.

Meanwhile, in some other works, an efficient image retrieval technique, which uses dynamic dominant colour, texture and shape features of an image, have been proposed. These studies have proposed CBIR system based on Dominant colour, Gray Level Co-occurrence Matrix (GLCM) and Gradient Vector Flow (GVF) [3]. They have claimed that their work has focused on global features, because low level visual features of the images, such as, colour, texture and shape are useful to represent and to compare images automatically. They have considered that combining the dominant colour, texture and shape features not only be able to express more image information, but also describes image from the different aspects for more detailed information, in order to obtain better search results [3]. The way that they have presented the result is satisfying; however, the result shown is the comparative study between the single feature extractions, with all the three combined low level features extraction. Obviously the result is better with more features extraction.

Moreover, other works have developed CBIR methodology that uses Gabor filter for determining the number of regions of interest (ROIs), which influences the performance of feature extraction [4]. In the ROIs extracted, texture features based on threshold Gabor features, colour features based on histograms, colour moments in YUV space, and shape features based on Zernike moments are then calculated [4]. Their contributions towards automated and efficient feature extraction in local areas of images, and thus they focus on the local approach to CBIR. More importantly, they have reported that, user is not required to indicate regions or points of interest manually. The comparative study between combination of three features extraction and combination of two features extraction (colour & texture, colour & shape, texture and shape) has revealed that the combination of three features extraction gives higher result.

Similarly, Wei [5] has indicated that the combination of three features extraction has yielded better results than one feature extraction. They have deployed all features extraction that comply with MPEG-7 standard, which are Domain Colour Descriptor (DCD) for colour extraction, Edge Histogram Descriptor (EHD) for texture extraction and

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Discrete Angular Radial Transform (DART) for shape extraction and they have claimed that these are fast and more in line with the requirements of human visual experience.

Based on all studies mentioned earlier that combine three low level features (colour, shape and texture), the different with our work is we have deployed compact descriptor that has managed to give higher accuracy with smaller requirements and storage. Also, in most retrieval systems that combine three features types such as, colour, texture and shape, independent vectors are used to describe each kind of information. It is possible to achieve very good retrieval results by increasing the numbers or the size of the descriptors, but this will lead to increase the storage requirements and the computational time. In this paper, we have introduced three compact composite descriptors incorporate colour, texture and shape information into one feature vector, while keeping their sizes as small as possible. The descriptors are Colour Layout Descriptor (CLD), Local Binary Pattern (LBP) and Fourier Descriptor (FD). The basic difference between CCDs and other descriptors in the literature lies in the fact that, each of these descriptors is determined for a different type (in terms of content) of image [1].

The reminder of this paper is organized as follows: Section II provides an overview of related work on retrieving images using more than one image features. Section III explains the feature extractions for each image feature (colour, texture and shape). The section IV discusses the techniques available in CBIR and section V describes the implementation. Section VI discusses the results based on the evaluation using the Euclidean Distance measurement. The results are discussed in two metrics. The first is the evaluation on the effectiveness in terms of precision and recall, and the second one is the comparison of other similar study using the same database. Section VII presents the conclusion.

III. Feature Extractions

Feature extraction is the main component in image retrieval. In fact, it is the first task in CBIR, where the feature vector is generated to accurately represent the content of each image in the database. The feature vector compared with the original image size is relatively small due the mathematical based information stored, rather than the pixel value of the image. Based on the visual content, the feature can be categorized into general features and domain specific features. The general features or referred as primitive features include colour, texture and shape feature, while the domain specific features are application specific and widely focuses on human faces and finger prints.

A. Texture Features

Even though there is no specific definition of texture, it refers to the visual patterns that have properties of homogeneity that do not result from the presence of only a single colour or intensity [6]. The texture information is important because it contains important information about the structural arrangement of surfaces and their relationship to the surrounding environment [7]. Texture can be regular or random. Most natural textures are random. The regular textures are composed of textures that have a regular or almost regular arrangement of identical or at least similar components. Irregular textures area composed of irregular and random arrangements of components related to some statistical properties [8] .

In the image, texture features capture information about repeating patterns. According to these authors [9], texture features are classified into three models as follows:

Statistical models: This group includes statistical moments of the gray-level histogram, especially, the second moment (the variance), uniformity and average entropy, descriptors (energy, entropy, homogeneity, contrast, etc.) [10]. Haralick et al. [11] have proposed the image gray level co-occurrence matrix, which is also classified in this model.

Spectral models: These are derived from the spectral density function in the frequency domain, Coefficients of a 2-D transform (e.g., the Wavelet transform) and Gabor Wavelet Transform [12] [10].

Structural models: The techniques that explain texture in terms of primitive texels [13]. This model is popular for artificial and regular patterns [10].

B. Shape Features

Shape representation normally looks for effective and perceptually important shape features based on shape boundary information or boundary plus interior content. Compared with colour and texture features, shape features are usually described after images have been segmented into regions or objects. Since robust and accurate image segmentation is difficult to achieve, the use of shape features for image retrieval has been limited to special applications, where objects or regions are readily available. The state of art methods for shape description can be categorized into two; boundary based or region based methods. The former uses only the outer boundary of the shape while the latter uses the entire shape region [14]. The most successful representations of these two categories are Fourier descriptor and Moment invariants. The main idea of Fourier descriptor is to use the Fourier transformed boundary as the shape feature [15][16]. Meanwhile the main idea of Moment invariants is to use region-based moments, which are invariant to transformation as the shape feature.

C. Colour Features

Among the primitive features mentioned earlier, colour feature is an extensively utilized visual attribute that plays an important role in image identification and extraction [17]. In fact, colour features are easy to obtain and often directly gain from the pixels intensities. It is relatively well known as robust to background complication and independent of image size and orientation. The three dimensional values of colour make it superior to the single dimensional grey values of mages [18]. This makes the colour as one of the most popular feature used in content-based image retrieval.

In computing the most common colours are red, green and blue. Usually colours are defined in three dimensional colour spaces. These could either be RGB, HSV or HSB. Most image formats such as jpg, bmp, gif use the RGB colour space to store information [19]. The main reason for this is because it preserves compatibility with computer displays. However, the RGB space has the major drawback in that it is not perceptually uniform [20]. In image retrieval systems, colour histogram is the most commonly used for feature representation. The colour histogram describes the proportion of pixels of each colour in an image, with simple and computationally effective manner. Colour histogram is obtained by quantizing image colours into discrete levels and then counting the number of times each discrete colour occurs in the image [21]. During retrieval, the histogram of a query image is compared with the histogram of all the images in the database. Other than colour histogram that is well adopted in CBIR research field, the colour moments are proposed to overcome the quantization effects of colour histograms [22]. Most information is concentrated in the low order moments, thus colour moment used the first three central moments of the colour component of the probability of each colour in HSV [22]. Nevertheless, both techniques colour histograms and colour moments have limited spatial information of colour location and pixel relation to other pixels. In order to solve the problems, other techniques are proposed such as, Colour Sets [23] and Colour Coherence [24]. In this paper, we have reviewed Colour Layout Descriptor as colour feature extraction. The reason we chosen this method is because of the compact size feature and ability to capture the spatial layout of the representative colours.

IV. Techniques In Content Based Image Retrieval

We have focused our research on using low level feature in CCD method due to the proposal to have lower computational time during the image retrieval process. With human vision, colour is the most attracted feature, compared with other feature. Also, colour feature are very stable and robust. It is not sensitive to rotation, translation and scale changes. However, results given by colour feature lacks of describing objects or things in the image and are not suitable for complex images with details. Thus, other study focuses on other kind of feature extraction such as, texture and shape that is able to overcome the issue raised by the colour feature. While, several image retrieval systems rely on only one feature for the extraction of relevant images, it has shown that an appropriate combination of relevant features can yield better retrieval performance [25]. We have found that many studies use the combination of colour and texture [19] [26] [27]. This combination works well due to the several factors such as, colour is easy to compute and texture would be able to capture the details of the image. Others use colour and shape, which normally require image segmentation [28]. Other studies have claimed that combination of colour and shape gives a higher accuracy but increases the computational complexity [29]. Also we have found that combination of texture and shape [30], was the least favourite method in image retrieval, due to higher processor and bigger size requirements. However, they have claimed such combination is suitable for medical image retrieval, to search for certain disease. Furthermore, medical image especially X-ray images, scan images, Magnetic Resonance Imaging (MRI) images are gray scale images with almost the same texture characteristics [31]. Thus the conventional colour does not appropriate to apply in medical images. Another study used combination of texture and shape feature to generate image mining [32] that would be able to produce knowledge on the image. One study shows that, with the texture and shape feature, they would be able to determine whether objects of an image is man-made (unnatural) or natural [33].The combination of all the three primitive features also contributes in CBIR research field, which shows that, such combination returns the image that are close to the images visualized by human [34] [35] [4]. Also, these combinations provide a robust feature set for image retrieval [2].However it is noteworthy that with combination of three low level features, the issue is slower processor due to bigger size of feature vector.

We have realised that with the combination mentioned above, the issue that remains unsolved is the computational complexity. Even they have managed to give higher accuracy and efficiency, at the end they require a higher computational and difficulty to remain the quality of the image. Thus, in order to give an alternative to the unsolved problem, we would like to implement Compact Composite Descriptor (CCD) that would be able to reduce the computational time. This descriptor has been designed with particular awareness to their size and storage requirements, keeping them as small as possible, without reducing their discriminating ability. The proposed descriptors are compact; however they incorporate colour, texture and shape information in one vector value. In our work, we have deployed Colour Layout Descriptor (CLD) for colour extraction, Local Binary Pattern (LBP) for texture extraction and Fourier Descriptor (FD) for shape extraction.

V. Implementation

A. *Colour Feature Extraction: Colour Layout Descriptor (CLD)*

The CLD captures the spatial layout of the representative colours on a grid superimposed on a region or image. The representation is based on coefficients of the Discrete Cosine Transform (DCT). The function of the CLD basically is in the image-to-image matching and video clip-to-clip matching. The extraction of the descriptor consists of four stages [36][37] such as; Image partitioning, Dominant colour selection, DCT transform and Non-linear quantization of the zigzag scanned DCT coefficients.

1. Image Partitioning

For the first stage, the image partitioning basically divides the image into 64 blocks (8 x 8), to guarantee the invariance to resolution or scale.

2. Representative colour selection

Once the image has been partitioned, the next stage is to select single representative colour from each block. Normally the most recommended method to select the representative colour is to use the average of the pixel colours in a block. This method is simpler and the description accuracy is sufficient in general. Also, at this stage, the conversion colour space from RGB to YCbCr is applied.

3. DCT Transformation

At this stage, the luminance (Y) and the blue and red chrominance (Cb and Cr) are transformed by 8x8 DCT, so three sets of 64 DCT coefficients are obtained.

4. Zigzag scanning

At this final stage, a zigzag scanning is performed with these three sets of 64 DCT coefficients, based on the schema. The purpose of the zigzag scan is to group the low frequency coefficients of the 8x8 matrix. Finally, these three sets of matrices correspond to the CLD of the input image.

B. Texture Feature Extraction: Local Binary Pattern (LBP)

The LBP originally appeared as a generic texture descriptor. In order for the LBP to implement the steps, it divides the examined window to cells (e.g. 16 x 16 pixels for each cell). For each pixel in a cell, the neighbours around the cell (top left, left middle, left bottom, right top) will be compared with the pixel. Normally the movement follows the pixels along a circle either in clockwise or counter-clockwise. The operator assigns value 1, if the centre pixel's value is greater than the neighbour. Otherwise, the value is 0. This gives an 8-digit binary number, which is then converted to decimal for convenience. These values are computed using histogram and when necessary the histogram are normalized. Then, concatenate normalizes histograms of all cells. Thus, this gives the feature vector for the window. In other words, given a pixel position (x_c, y_c), LBP is defined as an ordered set of binary comparisons of pixel intensities between the central pixel and its surrounding pixels.

LBP is one of the best texture descriptor for texture features. It is invariant to monotonic changes in gray-scale and fast to calculate. Its efficiency originates from the detection of different micro patterns (edges, points, constant areas etc.). LBP has already proved its worth in many applications [38].

C. Shape Feature Extraction: Fourier Descriptor

Fourier descriptor explains the shape of an object with the Fourier transform of its boundary. There are three types of contour representation as follows [39]:

1. Curvature

The curvature *K(s)* at a point *s* along the contour is defined as the rate of change in tangent direction of the contour

2. Centroid distance

The centroid distance is defined as the distance function between boundary pixels and the centroid (X_c, X_y) of the object:

3. Complex coordinate function

The complex coordinate is achieved by representing the coordinates of the boundary pixels as complex numbers

The Fourier transform of these three types of contour representation generate three sets of complex coefficients and represents the shape of an object in the frequency domain. The lower frequency coefficients describe the general shape property, while the higher frequency coefficient reflects the details of the shape. In order to achieve rotation invariance, only the amplitudes of the complex coefficients are used and the phase components are discarded. Also, to achieve scale invariance, the amplitudes of the coefficients area divided by the amplitude of DC component or the first nonzero coefficient.

VI. RESULT ANALYSIS

A. Database

In this study we have used WANG database [40]. This database is a subset of the COREL database of 1000 images. Images in the same row belong to the same class. All images are divided into 10 classes. Also, this database has been widely accepted as one of reliable database for testing in CBIR systems [41], due to the fact that the size of the database and the availability of class information, which enables performance evaluation. Furthermore, others use this database for classification experiments.

B. Performance Evaluation Metrics of CBIR

In order to evaluate the performance of retrieval accuracy of the proposed system, a pair of precision-recall is used. This is because precision-recall is able to provide significant result when the database type is identified and has been successfully used in earlier researches. The precision is a measure of the image retrieval system to retrieve only the relevant images. In the mathematical sense, precision is the fraction of the relevant images for an image query amongst all images retrieved [42].

Meanwhile, recall refers to the percentage of the total relevant images retrieved, and is mathematically defined as the total number of retrieved images from all the relevant images. A perfect recall score of 1.0 means that all relevant images were retrieved by the search

C. Performance on Test Image

In this performance test, we have evaluated the effectiveness of our proposed approaches of CCD by summing up the Euclidean distances between the corresponding features in their feature vectors. We have randomly selected 3 images from different classes; Elephants, Buses and Dinosaurs. Each query returns the top 8 images from the database. Figure 1 shows the precision and recall graph for query photo of elephant. Note that, the graph depicted below, is considered as almost a normal curve for precision and recall graph.

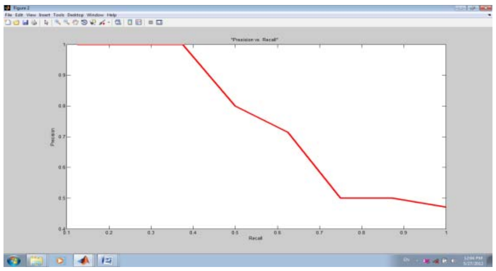

Figure 1: Precision and recall graph

The first three images are similar to the query image and retrieved from the same class. Therefore, the value of precision is 1 for all the first three images and the value of recall is between 0.1 and 0.4. The following three images displayed on the screen shows three different images from three different classes. Thus we can clearly see the line gradually drops down vertically. It shows that the lower precision has received the higher value of recall. The last two images come in same class, thus the value of precision is almost the same in which the graph's line goes horizontal.

Figure 2 shows the relation between precision and number of images retrieved. The shape of the graph shows that, the first three retrieved images are the most similar images to the query image. Then the value of precision gradually decreases, while the number of images retrieved is increasing. However, the graph stopped at the number 17, due to the fact that the images onward are not similar, in which the value of precision would heading close to zero.

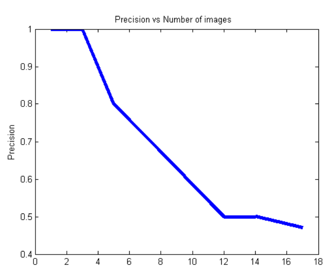

Figure 2: Precision and number of images retrieved

Also, we have tabulated results for average precision in table 1, which are obtained from other studies that use same database for their result analysis. The first author [43] presents their result in image retrieval using a combination of three low level feature extractions (colour, texture and shape). They have deployed the extended version of co-occurrence histogram for colour and texture extraction. For the shape extraction, they have used Gradient Vector Flow. Even they have claimed that they have produced a robust feature set for image retrieval, unfortunately they are not suitable for larger and dynamic database due to huge size of feature extraction.

TABLE I. AVERAGE PRECISION FOR EACH CLASS IN DATABASE COMPARED WITH OTHER WORK

Class	**J.Pujari & P. Hiremath** (Pujari, 2007) [43]	**A.Hafian & Zavidovique** (Hafiane, 2008) [44]	**Hamid A.J.** (Hamid, 2011) [45]	**Our Proposed Algorithm**
Tribe	54	44.1	32.3	45.4
Beach	38	30.6	61.2	66.2
Buildings	40	38.2	39.2	41.7
Buses	64	67.6	39.5	48.6
Dinosaurs	96	97.2	99.6	100
Elephants	62	33.8	55.7	69.3
Roses	68	88.8	89.3	90.9
Horses	75	63.2	65.2	63.6
Mountains	45	31.3	56.8	64.3
Food	53	34.9	44.1	53.2

The second author [44], has included the semantics in image retrieval. The author has presented a technique for image retrieval using Local Relational String (LRS) for a cue and mutual region matching for similarity measure. The LRS was shown to combine local information with global description to both colour and texture characterisation. Despite high discriminative properties, the LRS alone does not efficiently retrieve image. Meanwhile, the third author [45] has claimed that, the result produced by his work has managed to overcome the other two studies. The CLD in his work is compact in size, however the Gabor filters are well known for contributes to higher processor. Thus, our proposed method gives a higher average precision in various images than the other three methods did. This is due to the Compact Composite Descriptor, which is smaller in feature vector size and lower processor.

VII. CONCLUSION

This work had studied and merged three kind of low level feature (colour, texture, shape) extraction in Compact Composite Descriptor method. In order to develop the method, we had implemented the three functions for each of low level feature. The method was fully developed using Matlab code and tested with the query image obtained from the database. Results obtained from three different kinds of query images were satisfying, which shows the net precision is 64.3%. Finally the average of precision recall from our work had been compared with other studies that use the same database. The comparative analysis had proved the supremacy of our study.

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