mv number: Effective Key to Represent Images

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ABSTRACT

Recent research has given more importance on the optimization of the indexing structure; however there is a great need for research in the area of image representation for efficient retrieval. In this paper we present a method for reducing dimensions in multi-dimensional multimedia data while preserving similarities between different images. We propose to reduce the multi-dimensionality of the feature vectors to a single unique key called the mv number. Using this mv number as an effective key to represent image, we could achieve better efficiency in image matching and retrieval.

Keywords

Image representation, Dimensionality Reduction, Multi Dimensional Feature moments, Image retrieval.

1. INTRODUCTION

Content - based image retrieval helps users to retrieve relevant images from image databases based on their contents. There are numerous image retrieval algorithms already developed [Con92a, Jou95a, Con96a, Con04a, Con05a]. Most of these techniques attempt to characterize the image into a set of features or feature moments. These feature moments would act as matching factors or criteria for retrieval purposes. Traditionally these feature moments were extracted for low-level characteristics. However these low level feature moments fail to correlate high level characteristics. We try to capture the characteristics using feature moments derived through wavelet analysis techniques, which correlate to high and low level characteristics of the image. The feature moments thus derived are multi-dimensional, which creates complexities in indexing of images in databases for efficient matching and retrieval. In this paper, we propose a method to reduce the dimensionality of the feature characteristics which represent the image for matching purposes. We represent an image using a single unique key called the mv number in order to minimize the effort and computation required for forming clusters. An important aspect of this method is automatic rank ordering of the members inside the clusters, which obviates the need for computationally expensive distance calculations in retrieval system. For robust retrieval, using the proposed technique would suffice the need for distance calculation since the retrieved results are rank ordered according to their closeness to the query image.

The paper is organized as follows: Section 2 surveys related work, Section 3 introduces the sequence numbering technique; Section 4 consists of test results. Finally, we conclude in section 5.

Short Communications proceedings ISBN 80-86943-05-4
WSCG'2006, January 30-February 3, 2006
Plzen, Czech Republic.

2. RELATED WORK

Images are now being represented in a more concise and precise manner for efficient searching and browsing. Color indexing is insensitive to scale, rotation and translation and it is also robust to occlusion and changes in camera view angle. However, one of the main disadvantages of color indexing is that only color information is stored and the spatial relationship between pixels is lost. Moreover color indexing scheme has proven to be a disadvantage for large image databases [Jou00a]. In [Con95b], researches have divided the image into several sub images and represented these sub images with their color histogram for indexing. This method is computationally expensive and storage overheads are very high. Researchers have used image segmentation to single out important regions for indexing [Con99a]. This however is a very complicated process in terms of feature extraction and matching.

Some researchers have incorporated the local spatial relations. In [Wor96a], each pixel is classified as coherent or non coherent, based on whether the pixel and its neighbors have similar colors. Such approach can distinguish widely scattered pixels from closely clustered pixels. A similar method, known as the color structure descriptor is defined in the MPEG-7 standard [MPG701]. An 8 X 8 mask is used as the structuring element to collect color statistics such that spatially highly scattered and closely clustered color pixels can be distinguished. In [Jou02a], connected pixels with similar colors are grouped together to form color blobs, and statistics of the color blobs' geometry properties are used to retrieve image. All the above methodologies deal with color statistics and spatial relationship between pixels to derive effective representation of images for efficient retrieval.

In [Jou98a], the researchers have used Hilbert space filling curves to map the multi-dimensional feature vectors of image onto a Hilbert Grid through which they build an indexing scheme called HG tree for searching. The multidimensional feature vectors are reduced to smaller dimensions using Hilbert space filling curves however the complexity involved in mapping these multidimensional feature vectors onto a Hilbert grid are high. In our recent paper [Con05a], we have used complex wavelet decomposition to decompose images and represent images using feature vectors for effective retrieval. Linear indexing was used on these feature vectors. We propose to reduce the multi-dimensionality of feature vectors to a single unique key with an objective to represent images.

3. KEY: mv NUMBER

In our previous work [Con05a], we have used sets of μ and σ values as effective representations of an image. These values are derived from the detailed coefficients of the decomposition technique discussed in [Con05a]. Complex wavelets with five scales of decomposition are used to derive 30 detailed coefficient matrices from which mean and variance pairs can be found for each of red, green and blue components of a colored image. Each coefficient matrix represents the behavior of that image at particular decomposition level for a particular orientation. Thus we try to map the variation in the image from every orientation in five decomposition scales. Thus, we can satisfactorily represent an image using set of μ and σ values.

We introduce a set of three parameters which could be used to reconstruct the feature characteristics (μ and σ).The three parameters are:

$$\alpha_n = \frac{\mu_n}{\sigma_n} \qquad (3.1)$$

$$\beta_n = \frac{\mu_n}{\mu_{n+1}} \qquad (3.2)$$

$$\gamma_n = (\mu_n - \mu_{n+1}) \qquad (3.3)$$

Where

$n = 1,2,....T-1, T$ = total number of feature vectors.

Fig 1(b) plots the α values for RGB with thirty features for each color of the image 1 shown in fig 1 (a). It is noticeable that for a given color, the α value remains almost consistent with minor fluctuations. With negligible loss in accuracy we can represent each color by a single value of α. Calculating the weighted average of these values:

$$\alpha = \frac{\sum_{i=1}^{n} \alpha_i \mu_i}{\sum_{i=1}^{n} \mu_i} \qquad (3.4)$$

Where, n = number of color components.

α plot of three images are shown in Fig 1(b), Fig 2 (a) and (b). The α curve of the two similar images follows a similar pattern; whereas the dissimilar image does not follow suit. This dissimilarity in curve characteristics would characterize the difference between two dissimilar images, hence we use α as a criterion for generating our sequence.

The β values measure the trend of the μ graph. They neither indicate the mean about which the curve fluctuates nor do they quantify these fluctuations. But every value indicates the change from the previous value. These values serve to differentiate between, say two curves of similar trend which fluctuate about different means.

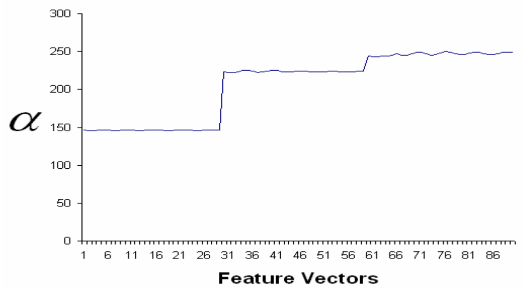
The γ value quantifies the change in the first two μ values for each color. Therefore using the γ value and the full set of β values the entire curve can be reconstructed. τ is a combination of β and γ:

$$\tau = (\beta, \gamma) \qquad (3.5)$$

β and γ values were calculated for the three images in Fig 1(a) . Fig 3 shows the plot of β versus γ. From fig 3, we can see that out of three images two were similar and third was a dissimilar image. The two similar images are clustered and the third is astray. It is evident from Fig 3 that images with similar β and γ values would be clustered

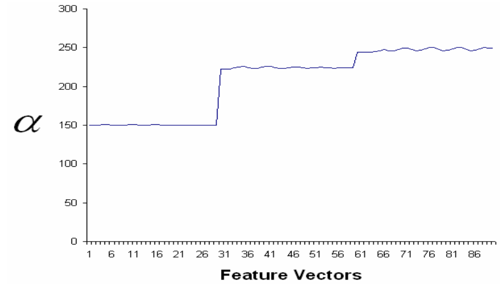
Image 1 Image 2 Image 3

(a)

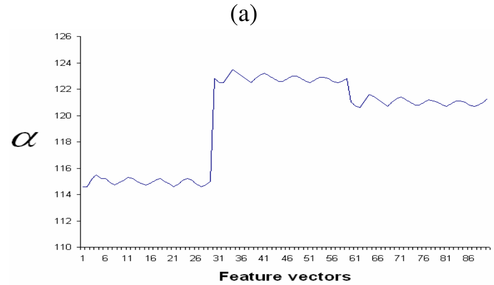


(b)

Fig 1. (a) Image 1, Image 2 and Image 3 (b) α characteristics of image 1



(a)



(b)

Fig 2. (a) α characteristics of Image 2, (b) α characteristics of Image 3

thus substantiating our claim that these are valid criteria for image characterization.

Thus, we assume that if a set of parameters can be used to reconstruct a particular distribution, then the set of parameters are unique to that distribution.

Thus multidimensional feature characteristics could be reduced to a set of few parameters which could be used for indexing and similarity calculations. Combining τ and α criteria would result in efficient mv numbering of the images thus resulting in better clustering. α and τ are combined to generate a 13 digit mv number. This scalar key thus approximates the reduction of the multidimensional feature characteristics to a one dimensional quantity. The mv number is a simple key representation of the image using the three proposed parameters i.e. Eqn 3.1, 3.2, 3.3.

4. EXPERIMENTAL SETUP AND TEST RESULTS

The experimental setup for testing the mv numbering technique was implemented in Linux on a Pentium PC. Coil 100 [10] database consists of color images of 100 objects taken in 72 different angles, thus resulting in a database of 7200 images in total For consolidating our technique we have extracted 30 images from the COIL 100 database. We manually classified the extracted images into two different groups. Fig 4 shows β vs. γ plot for these 30 images. We can see from the figure that the images are automatically clustered into two groups depending on their mv number. The area of these clusters could be bound by a threshold value. Any subtle changes in the image would reflect on its feature characteristics which in turn would also reflect on its mv number. However the change in the mv number would be proportional to the changes in the image characteristics itself. Changes in light, scale translation etc would result in very small changes in mv number there lending robustness in matching two similar images.

We have used a simple binary tree for indexing the database with mv number as the key for each image in the database. The root of the binary tree is a simple average of the mv numbers of all the images in the tree below. We have compared our test results with the HG tree [Jou98a].

The effectiveness of the indexing schemas with regard to searching was judged by measuring the number of memory accesses (read + write). Since the tree is stored in the memory, every calculation involving a value from the tree is counted as a memory access.

Even though HG tree has tertiary tree structure, it has more disk accesses for a given set of nearest neighbor search when compared to a simple binary tree with our proposed sequence number as a key for each image. Especially for low nearest neighbor queries, index structure with mv number as key has very low disk accesses. Effective and efficient clustering due to mv numbering technique is a major factor for the low disk accesses of the simple binary

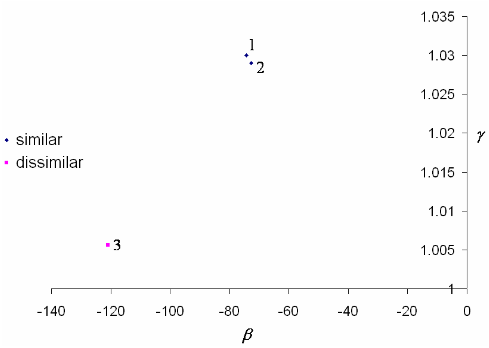


Fig 3. β vs. γ plot for the three images

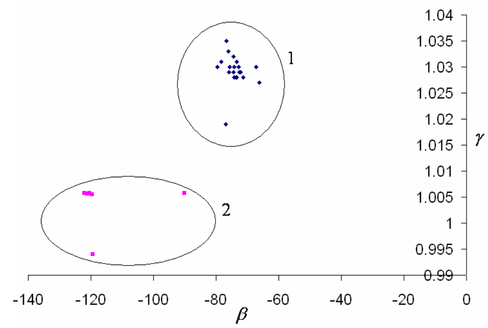


Fig 4. β vs. γ plot for 30 images.

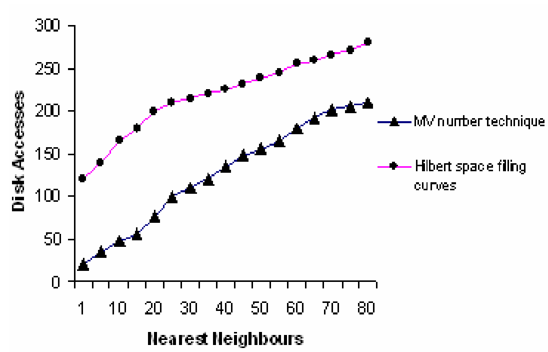


Fig 5. Disk accesses

index structure.

5. CONCLUSIONS

We have proposed mv numbering as a key for effective representation of images. Test results support our claim that this mv numbering technique helps in forming efficient and effective clusters. This cluster formation would minimize the effort and computation required for creation of clusters. For robust retrieval, the proposed technique would suffice the need for distance calculation since the retrieved results are ranked ordered according to their closeness to the query image. Thus, mv numbering could be used as an effective and efficient image representation in matching and retrieval systems. In our future work, we would research on feasibility of the key mv in different types of indexing structures for effective and efficient retrieval and also research on better indexing structures in which this key technique would yield optimum performance.

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