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CONTENT BASED IMAGE RETRIEVAL USING EUCLIDEAN AND MANHATTAN METRICS

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Abstract

Searching test image from image databases using features extraction from the content is currently an active research area. In this work, we present novel feature extraction approaches for content-based image retrieval, when the query image is color image. To facilitate robust man-machine interfaces, we accept query images with color attributes. Special attention is given to the similarity measure with different distance matrices properties since the test image and object image from database finding the distance measuring. Several applicable techniques within the literature are studied for these conditions.

The goal of this paper is to present the user with a subset of images that are more similar to the object image. One of the most important aspects of the proposed methods is the accuracy measurement of the query image with different database images. The method significantly improves the feature extraction process and enables it, to be used for other computer vision applications.

1. Introduction

Content Based Image Retrieval (CBIR) is a set of techniques for retrieving semantically relevant images from an image database based on automatically derived image features [1]. The computer must be able to

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retrieve images from a database without any human assumption on specific domain (such as texture vs. non texture or indoor vs. outdoor).

One of the main tasks for (CBIR) systems is similarity comparison, extracting feature signatures of every image based on its pixel values and defining rules for comparing images. These features become the image representation for measuring similarity with other images in the database. Calculating the difference of the feature components for query image and different database images.

Early CBIR methods used global feature extraction to obtain the image descriptors. For example, QBIC [11], developed at the IBM Almaden Research Center, extracts several features from each image, namely, color, texture, and shape features. These descriptors are obtained globally by extracting information on the means of color histograms for color features; global texture information on coarseness, contrast, and direction; and shape features about the curvature, moments invariants, circularity, and eccentricity. Similarly, the Photo-book-system [6], Visual-Seek [7], and Virage [2], use global features to represent image semantics.

Image database is one of the centerpieces for distributed multimedia systems. In general, an image database system is an intelligently combination of the following three major components:

- image processing,
- storage, retrieval, and management,
- user interface.

The first component deals with processing for the extraction of information from original images, while the second component is providing efficient tools for storing, retrieval, and managing of image data. Querying the database needs a simple and user friendly interface, which is the responsibility of the third component.

2. Related Work

2.1. Pixel domain techniques

Typically, visual indexing techniques are based on features, which are extracted directly from the pixel domain. These include visual features that the human visual system can easily recognize. Working in this domain is more intuitive and does not require us to transform and re-transform the images at the store and retrieving stages, respectively. Here, we review the most important image clues in the pixel domain, which are color, texture, shape, spatial relation, and sketch.

2.2. Compressed domain techniques

The large volume of visual data necessitates the use of compression methods. Multimedia databases usually store the visual content in compressed form and most images are stored using existing compression techniques. In order to reduce the cost of decompression of the image data and applying pixel domain techniques, it may be more efficient (if applicable) to index visual information in the compressed form. This approach often has a lower cost for computing and storing the indexes.

Compressed domain indexing is broadly classified into two main categories: spatial domain, and transform domain techniques. The major techniques in the first category are vector quantization [8] (VQ) and fractals. The second category is generally based on image transformation techniques including DFT [9] (discrete Fourier transform), DCT (discrete cosine transform), sub bands/wavelets transforms, Haar transforms, and KLT (Karhunen-Loeve transform).

3. Proposed Work

The goal is to present the user with a subset of images that are more similar to the query image. New affine transform invariant feature extraction techniques are proposed to improve retrieval performance and reduce the extraction and search times. The techniques are tested both generally for multi-component images and particularly for any pictures. The solutions are discussed for each specific application. Finally, content-based image retrieval [3], which explores image retrieval from databases using different distance metrics, is investigated on an individual basis.

Two different approaches are based on CBIR, i.e., Pixel domain based and another one is compressed domain based for general image retrieval. Here, the database images consist of multiple complex images within an inhomogeneous background. One of the methods is an improved version of the another, which increases retrieval performance. Both techniques exhibit their better task and perform better result.

Our approach is to retrieve the image from the frequency domain method. By this method, we firstly apply the color image conversion, i.e., in the form of RGB. We must have to apply the color conversion technique first with the help of color model, i.e., HSV (Hue, Saturation, and Value). The MATLAB code is so much helpful for us for converting the image color in HSV format. After converting, we are selecting the blocks of the picture, which is helpful for finding the distance measure. Here, we apply the similarity measure between two images with the help of different metrics such as Euclidean metrics so on.

Firstly, we take two images and make the blocks into it, which requires to measure the distance of metrics by image 1 find the Euclidean distance that is called *Euclidean* 1. Now, again find the distance of another image, we get the Euclidean distance that is *Euclidean* 2. After it, we can find the distance with the help of these two distances, which is called *Manhattan metrics*.

4. Algorithm

4.1. Preprocessing

Step 1. Input various object images.

Step 2. Create 4*4 block matrices.

Step 3. Calculate mean of block matrices.

Step 4. Concatenate all the block matrices obtained from Step 3.

4.2. Feature extraction

Step 5. Convert block matrices of query image "f" in RGB space and object image "g" in HSV space.

Step 6. Extract feature vector from HSV space.

4.3. Similarity Measure

Step 7. Calculate Euclidean distance, i.e., Euclidean 1 (D_2) as

$$D_2(f, g) = l_2(f, g) = \sqrt{\sum_{i=1}^{N} (f_i - g_i)^2}.$$

Step 8. T_i is the query image and O_j is one of the images from the database. Compare the test image with different images from image database ranging from O_1 to O_N, where the range of the images are from 1 to N. Go on comparing the query image until we find an image O_j such that $(T_i == O_j)$, i.e., Euclidean distance is zero or if not so, report failure.

Step 9. Now, we have Euclidean distance metrics related to query image and the various 'N' object images in the data base.

Step 10. Then, calculate Manhattan distance (D_1)

$$(D_1)(f, g) = l_1(f, g) = \sum_{i=1}^{N} |f_i - g_i|.$$

Step 11. Evaluate accuracy as

$$\text{Accuracy} = (Tp + Tn)/N,$$

$$N = Tp + Fp + Tn + Fn,$$

%, where Tp = Count of true positive;

Fp = Count of false positive;

Tn = Count of true negative;

Fn = Count of false negative;

End

5. Data Set and Results

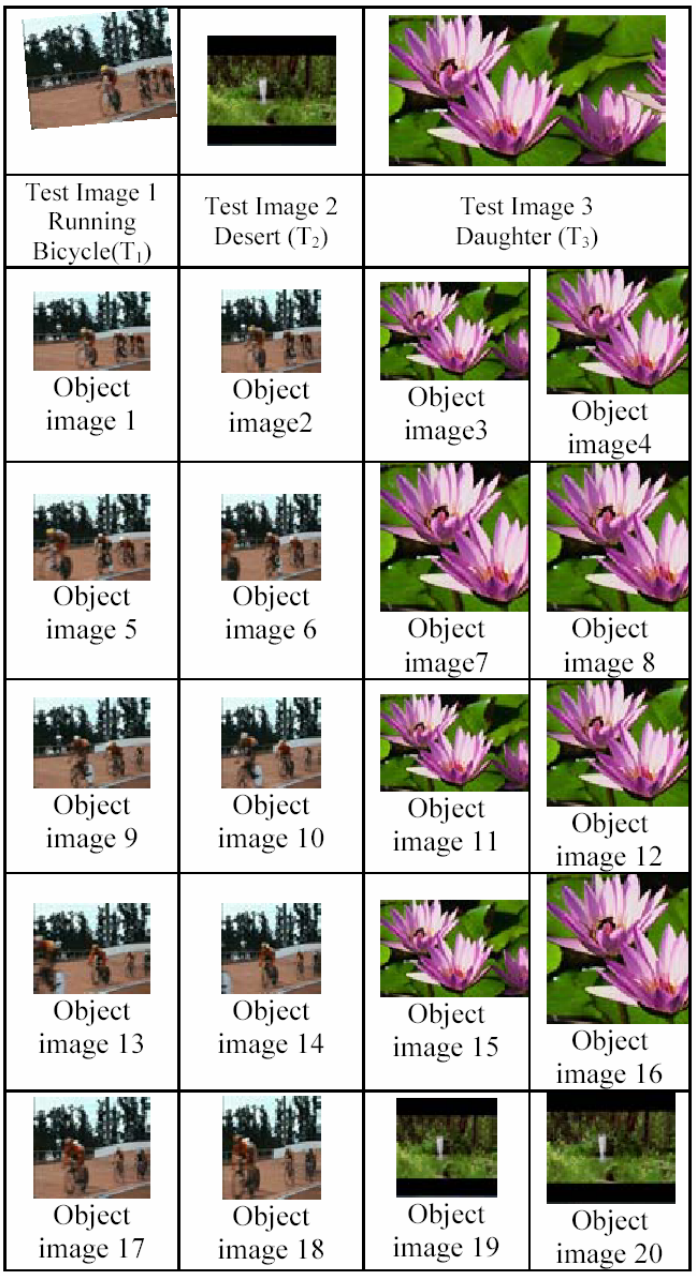

Figure 1. Test image data.

Object Images	Test Image 1	Test Image 2	Test Image 3
	Object image 1		
		Object image 3	
			Object image 6
	Object image 7		
		Object image 9	Object image 4
	Object image 2	Object image 5	Object image 8

Figure 2. Image categorization through evaluation of object images and Test image 1.

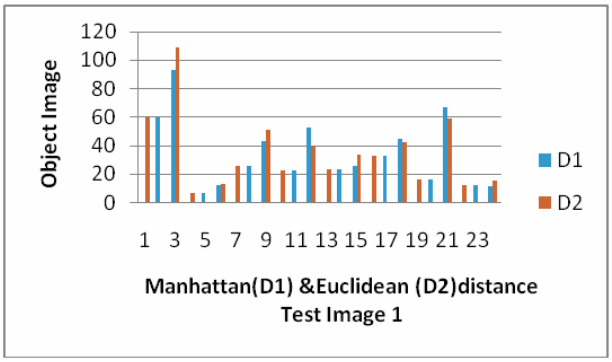

Figure 3. Graph shows the Euclidean distance ($D2$) and Manhattan distance between Test image1 and Object image database.

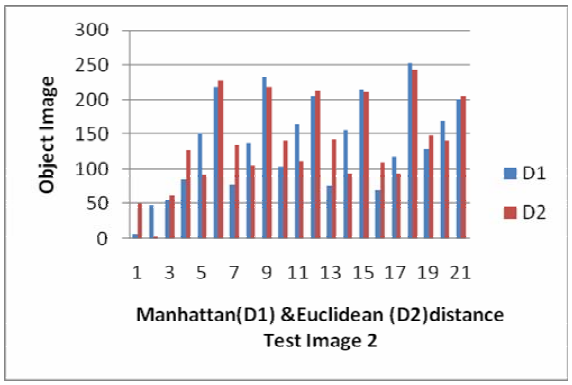

Figure 4. Graph shows the Euclidean distance ($D2$) and Manhattan distance between Test image 2 and Object image database.

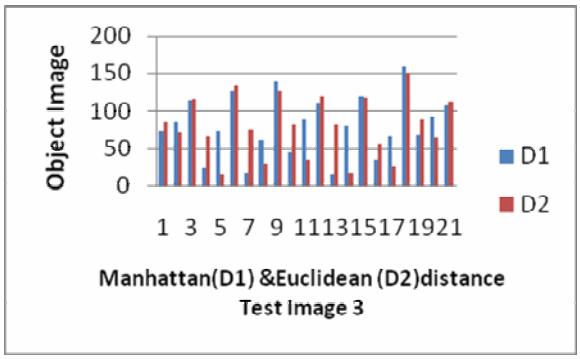

Figure 5. Graph shows the Euclidean distance ($D2$) and Manhattan distance between Test image 3 and Object Image database.

6. Conclusion

In conclusion, this paper has presented several novel techniques for invariance feature extraction used in the CBIR. They achieve significant improvement in retrieval accuracy, since Euclidean, and Manhattan distances give the relative comparisons in their features vectors. The proposed techniques describe the similarity match between object images and test images. The test images of the color feature must match with the color feature of the object images. The proposed methods are based on the distance similarity matrices of images. We use different matrices such as Euclidean, Manhattan, which have been suitable for general images.

7. Future Work

Possible improvements and further studies on the proposed methods are addressed below:

- In the distance similarity measure method, the number of same images could be assigned dynamically. This means, we are calculating the distance with the pixels for Euclidean 1. This would improve the performance but might slow down the feature extraction process. Moreover, variation in feature vector dimension makes the image matching complex. One solution to this problem can be partitioning the database images according to the respective feature vector dimension. In the matching process, the features extracted from the query image need to be compared only with the similar dimension features of the database images.
- The Manhattan distance must be calculated in above, can be applied to the Eigen vector method as well. Here, it indicates dynamically assigning an appropriate sector size for different images based on the existing density of pixels. The problem of complex matching will arise, which could be solved as described.

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