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Image Search Engine for CBIR using HSV Histogram Colour features

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Abstract

By applying the Content-based Image Retrieval (CBIR) technique, a picture search engine delivers the most relevant image based on the query image. This approach quantifies the dataset by extracting HSV colour histogram information from each image using an image descriptor. When a query image is supplied, it compares the chi-square distance similarity to discover related photos. Here in this paper, Stanford Dog Dataset is used to extract HSV colour features and compared them with a query image.

Keywords: *Image Retrieval, Content-based image, query image, search image, HSV*

1. Introduction

In general, there are two types of picture search engines: meta-data search and example search. Image search engines that quantify the contents of a photograph are known as Content-Based Image Retrieval (CBIR) systems. CBIR is a common acronym in academic literature, although it's actually just a fancy way of saying "image search engine," with the added poignancy that the search engine is completely based on the contents of the image, with no language annotations.

Search by Meta-data

Searching via meta-data differs just a little from the above-mentioned keyword-based search engines. Meta-data systems hardly ever look at the image's actual content. Instead, they rely on textual cues like (1) human annotations and labelling, as well as (2) automatic contextual indications like the text that shows next to an image on a webpage. When a user uses a search by meta-data system, they enter a query, similar to how they would in a regular text search engine, and photos with comparable tags or annotations are returned. This class of example is depicted as follows in figure1.

Figure 1: Search by meta-data (www.pyimagesearch.com)

Search by example

On the other hand, search by example systems relies simply on the contents of the picture; no keywords are anticipated to be given. The image is examined, measured, and saved in order for the system to return comparable photos during a search. An example of this class is shown in the following figure 2.

Figure 2: Search by example (www.pyimagesearch.com)

2. Literature Review

There is a vast quantity of data available, and every day, terabytes of data are created [1]. To obtain photos, the prior strategy relied on a text or annotation-based approach [2]. The process of change is the first component of CNN. The authors [3] use a state-of-the-art deep learning approach to develop a deep learning system for content-based image retrieval (CBIR) and conduct a complete set of empiric investigations for a range of CBIR tasks. A color-based SIFT comparison approach for partial-duplicate picture retrieval that recovers the image's prominent region with plentiful visual material [4]. [5] introduced a new strategy for bundling SIFT features into local groups utilising the MSER (Maximally Stable Extremal Region) detector, as well as a relative ordering geometric limitation for bundled features. The SIFT descriptor outperforms numerous other descriptors in studies on local descriptors [6]. In [7], we use the newly proposed colour histogram descriptor as a source of additional information that might be crucial in feature matching. SIFT descriptors used in many partial duplicate image retrieval systems [8]. The authors [9] proposed a method for content-based saliency regions for detecting sub-regions of high resolution image in the query image. In the recommended approach for the CBIR scheme, the DL-CNN architecture was applied for enhanced attribute representation for word pictures over previous retrieval systems [10].

3. Architecture

The following figures3 and 4 explains the process of CBIR and retrieval of an image using search.

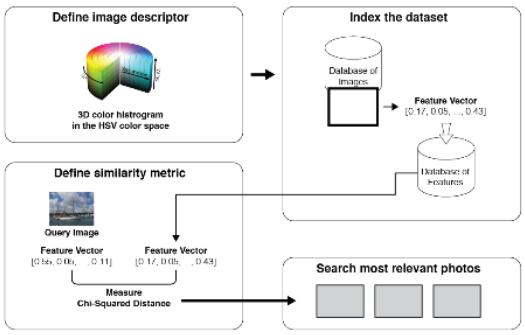

Figure 3: CBIR process

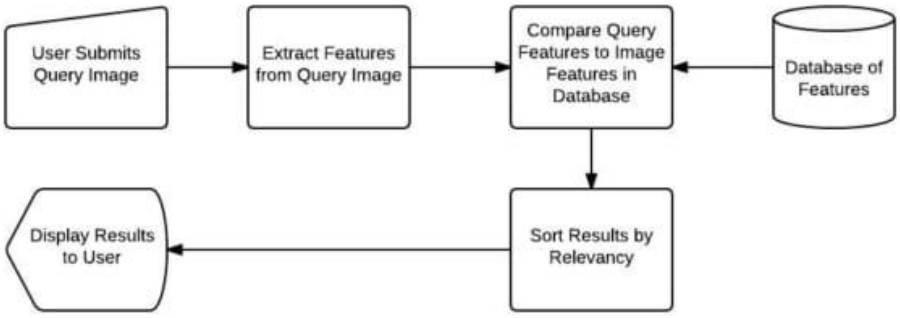

Figure 4: Performing an image search on CBIR.

We'll use a basic yet effective picture description called the colour histogram to develop this system. We'll be depending on the image's colour distribution by using a colour histogram as our image descriptor. Images with comparable colour distributions will be grouped together where applicable. Even though the contents of two photographs are drastically different, they will be regarded "similar" if their colour distributions are comparable.

4. CBIR Image Searcher

4.1 Define Descriptor

Instead of RGB colour histogram, here we are using 3D HSV colour histogram. As RGB values may not well appear to human eyes, and HSV colour space is mapping the pixel intensities into a cylinder. Once we selected the colour space then define the number of bins for histogram, and it will estimate the probability density of underlying function. In the HSV colour space, we'll use a 3D colour histogram with 8 bins for the Hue channel, 12 bins for the saturation channel, and 3 bins for the value channel, resulting in a total feature vector with dimensions of 8 x 12 x 3 = 288. This means that every image in our dataset will be abstractly represented and quantified using simply a list of 288 floating point integers, regardless of its size (36 × 36 pixels or 2000 x 1800 pixels).

4.2 HSV Colour Feature Extraction

"Indexing" refers to the process of extracting features and storing them on permanent storage. Initialize color discriptors with H, S, and V as 8, 12, and 3 values. The feature vector contains representations for each of the 5 image regions with 8X12X3=288 entries. For a given 5 entries, the overall feature vector is 5X288=1440 entries. These entries need to quantify the image for all the features and here the 805 images have been indexed.

4.3 Search

Here, we use similarity among the features of the vectors. The similarity between the two images can be calculated. The search method uses two parameters as query features extracted from the query image and a limit for the maximum number of resulted images shown. The indexed image's colour histograms are extracted, and the chi-squared distance is used to compare them to the query image's characteristics. Images with a chi-squared similarity of zero are considered identical. The photos are regarded to be less similar to each other as the chi-squared similarity value grows. The chi-square algorithm is shown in the following figure5. The chi-square calculation formula is shown in the equation1.

$$\chi 2 = \sum(Oi - Ei)2/Ei \qquad (1)$$

where Oi is the observed value and Ei is the expected value.

Input: query image histogram: x
sample image histogram: y
number of histogram bars: N
Output: distance between two histograms: dist
1. **for** i = 1 **to** N
2. $temp(i) = (x_i - y_i)^2/(x_i + y_i)$
3. **end**
4. dist $= \sum_{i=1}^{N} temp(i)$

Figure 5: Chi-square algorithm

4.4 Perform Search

Uses them in conjunction with each other to build a full-fledged Content-Based Image Retrieval System.

5. Results and Discussion

5.1 Data Set Description

The INRIA Holidays Dataset used for this paper. It consists of various vacation trips from all over the world, including photos of the Egyptian pyramids, underwater diving with sea-life, forests in the mountains, wine bottles and plates of food at dinner, boating excursions, and sunsets across the ocean. The number of training images per class is varied from 1 to 100. The accuracy of each class is compared for 15 and 100 training images per class. Figure 6 shows the sample image from the dataset.

Figure 6: A sample image of dataset.

The experiment is conducted on 8GB RAM and 512GB SSD on i5 core system. The results were found encouraged by submitting a query. The first image is containing boats on the sea. The second image is query image of the Egyptian pyramids. The third query image is underwater adventure. The table1 shows the mean averages of precision and recall of the various input images. The table 2 gives the comparative results of various other methods.

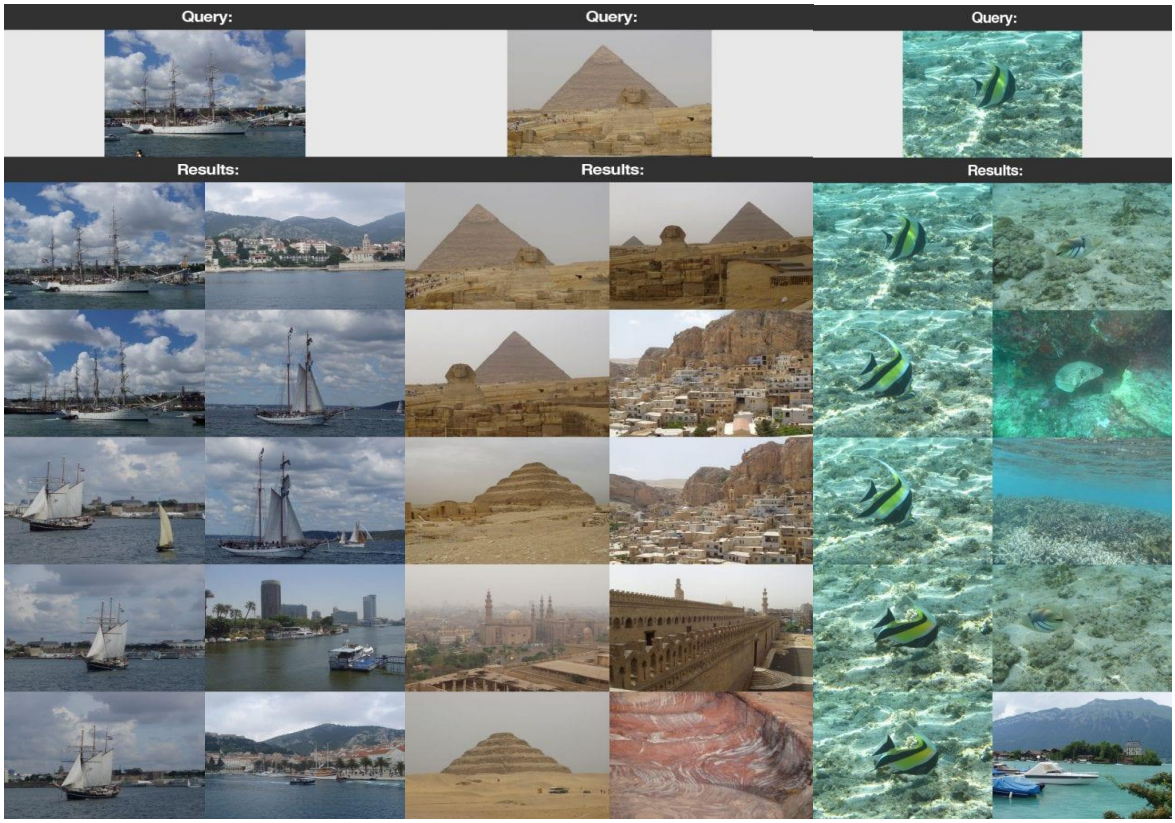

Table 1: Performance of images of the dataset

Input Image	mAP	mAR
Pyramid	86.14	90.34
Boats on the sea	82.85	86.45
Underwater adventure	88.91	91.34
Forests in the mountains	83.23	85.78
Average	85.23	88.53

Table 2: Performance comparison

Input Image	mAP	mAR
Colour Histogram	68.76	71.56
DWT	79.76	78.42
HSV Colour Histogram	88.98	89.54

6. Conclusion

This paper is proposed HSV colour feature model for CBIR system to learn efficient images. The authors carried out an empirical experiment on the data very effective. By using the mAP and mAR measures, it is observed that the algorithm found the good results on CBIR. It provides mAP and mAR of 88.98 and 89.54 respectively.

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