Algorithm and Data Structure Coursework: PCA And K-Means for R-tree Based Similar Image Search

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ABSTRACT

This project implements a similar image search engine based on R-Tree and several image features. We explores the performance of three major features, i.e., color moment (by color distribution), principal component analysis (PCA, by image rough shape), and K-Means (by image details). We analyzes the correctness of different features, and the relation between features and R-Tree node accessing times. We try different insertion orders and similarity functions for R-Tree, and summarize their effect with different features.

We made our work open, and the full project codes can be found at `https://github.com/caiwaifung/lastcourse`.

Keywords

R-Tree, Similar Image, PCA, K-Means

1. INTRODUCTION

Similar image searching is a popular problem in computer vision and data science. Many nice approaches have been serving the public online, like Google, Baidu, etc. The idea of fast and nice similar image searching usually splits into two parts: feature extraction and close points finding.

Feature extraction: When calculating the similarity between two images, we must find their simplified representation before we could compare, because image dataset is too large. Usually the representation is an array of integer or real numbers (feature vector). By representation, the similarity can be simplified by some simple math operations between the representation instead. The way to represent an image is called feature extraction. A well designed feature should have two properties.

- Small. Smaller feature size means less stress on computation and storage.
- Accurate. Similar images will have similar features, while irrelated images have discriminable features.

Close points finding: After all images have been turned into feature vectors, the problem now is to maintain a set of vectors (image pool), and when take a query vector (query image), find the top several closest vectors in the set for the query one. This problem usually occurs in two scenario:

- Sparse. E.g., many elements in a feature is zero, only some appears non-zero. Like the word count for a article. Usually an article will not cover all vocabularies we cares. We usually use inverse lookup based data structures to solve sparse feature similarity searching problem.
- Dense. The dimension of features are usually small, and most elements do not have default values that appears in a considerable probability. The features studied in this project are all dense features. We usually use K-D Tree based data structure to solve dense feature similarity searching problem. R-Tree is a variation of K-D Tree that is designed for disk structure.

2. FEATURE FINDING

2.1 Low Level Features

We can design features for general images, with no training phase. Such features are called low level features. However not to misunderstand, low level features can be very strong.

Color moment is a low level feature: it considers each pixels color space, RGB or HSV, and calculates the mean, variance, and skewness for each parts. We included the given color moment feature in our project.

$$M_1^H = \frac{1}{w \times h} \sum_{x,y} H[x,y] \tag{1}$$

$$M_2^H = \sqrt{\frac{1}{w \times h} \sum_{x,y} (H[x,y] - M_1)^2} \tag{2}$$

$$M_3^H = \sqrt[3]{\frac{1}{w \times h} \sum_{x,y} (H[x,y] - M_1)^3} \tag{3}$$

And similarly for $M_{1\ldots3}^S$ and $M_{1\ldots3}^V$. The final representation is $\mathbb{R}^9$:

$$\left\{ M_{1\ldots3}^H, M_{1\ldots3}^S, M_{1\ldots3}^V \right\}$$

This feature describes the color distribution of image, without regard to the pixel permutation.

There are many other way to design low level features like color space histogram, gradient distribution or histogram, or we can divide the image into determined districts, e.g. 3x3, and extract feature for each region, finally merge into a single long feature.

However, low level features usually takes fixed size (dimension) and not suitable for our study of R-Tree with different feature dimensions. So we tried to extract deeper features that is learned from the dataset unsupervisedly (The project guide forbids training feature with ground truth label).

2.2 Principle Component Analysis

A straight forward idea of comparing two image, is to resize them into an identical size $w \times h$, and compare the images pixel by pixel. We set $w = h = 32$ which we think manually examining images is still feasible. All images are resized to 32x32 in advance, with linear stretch if the ratio is not 1:1.

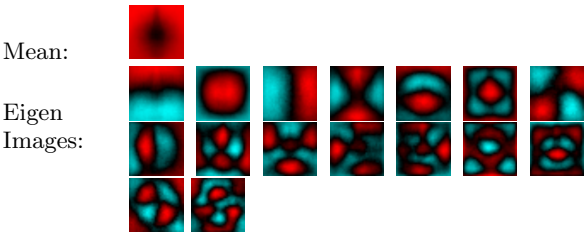
Because we already have color based feature, we leave out the color, and only use 32x32 0 255 grayscale images in this feature design.

Then, we can use a small set of 32x32 eigen images, as the principle component learned from the dataset, to describe any potential image as close as possible.

Every image can be written by a linear combination of several eigen images. Eigen images are orthogonal with each other, so by dot production, we can easily find the eigen base representation of a image.

PCA is to find eigen images in a way that first few eigen images will covers the most variance of images in the data distribution.

We list the average image and first few principle components found by PCA in our project:



Note: Red means possitive, Cyan means negative. Dark means less absolute value.

The advantage of PCA is we can select to use any number of eigen images, i.e., only use the first few most significant components to represent the whole image constitution. We used Numpy and Matlab in the training phase of PCA, which takes just few minutes on a personal computer.

2.3 K-Means

Many research in computer vision finds that the appearance of same patterns by convolution in image will help learning deep representation. K-Means is the basic way to find such patterns.

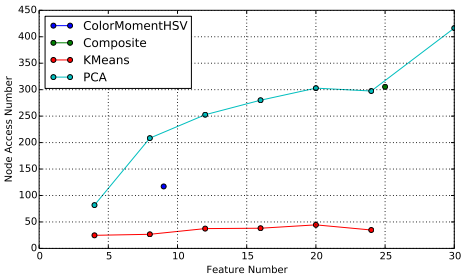


Figure 1: Node Access Number

First resize the images reserving the ratio to have the largest side length ≤ 32. Then we extract all 4x4 patches with RGB color space. So a patch contains 48 numbers, and for a resized image, there are at most $(32-4+1)^2 = 841$ patches. We normalize each patch vector by

- Subtract the average among all 48 channels.
- Normalize to a unit vector.

Then, we try to cluster all patches in the dataset (approximately 5613×841) using K centroids, for $K = 4, 8, 12, 16, 20, 24$.

Then we represent an image by K average distances between every centroid and all normalized patches that image has.

The training phase takes several hours, and that's why we only use 32 image side and 4×4 kernel.

2.4 Composite Feature

We also designed a composite feature: the concatenation of PCA16 and Color Moment. We adjust the scale of Color Moment by 0.1 to balance the feature variance.

3. DATA

There are 5613 images given. We first random shuffle the dataset to $r_{0\ldots5612}$, and split into two parts: pool set with 5000 size, query set with 613 size.

```
data1k: 0~999; data2k: 0~1999; data3k: 0~2999;
data4k: 0~3999; data5k: 0~4999; query: 5000~5612
```

4. R-TREE

We use the "rtree alternative package" implementation of R-tree. The wrapper `src/a.cpp` calls methods of provided R-tree class. Run `python src/run.py` to compile and run the program.

5. EXPERIMENTS

5.1 Node Access Numbers (Problem 1)

Table **??** lists the node access number in different cases.

Figure **??** shows the relationship between node access number and feature number under database of 5000 features. We can see that the number of access number increases while the feature number is increased.

Method and Feature Num	1000	2000	3000	4000	5000
Color Moment HSV 9	46.11	67.69	88.69	98.24	117.0
PCA 4	37.18	53.31	71.37	76.72	81.83
PCA 8	68.42	107.7	145.8	176.1	208.4
PCA 12	77.95	129.9	174.5	217.8	252.6
PCA 16	82.46	135.4	190.2	236.2	280.0
PCA 20	81.55	137.8	196.4	253.7	302.8
PCA 24	83.11	135.7	192.8	248.0	297.4
PCA 30	123.8	207.4	281.4	351.7	416.4
KMeans 4	**16.01**	**19.76**	**22.24**	**23.53**	**24.71**
KMeans 8	17.49	21.83	24.44	25.88	26.66
KMeans 12	20.90	25.76	30.96	34.85	37.43
KMeans 16	22.22	28.40	33.89	37.25	38.14
KMeans 20	25.25	35.26	39.25	39.67	44.48
KMeans 24	20.68	27.81	30.20	33.46	34.79
Composite 25	80.01	136.8	202.4	254.9	305.4

Table 1: Node Access Numbers

Method and Feature Num	1000	2000	3000	4000	5000
Color Moment HSV 9	153	174	178	190	195
PCA 4	116	130	133	141	151
PCA 8	158	170	172	176	183
PCA 12	181	190	199	205	208
PCA 16	181	198	205	206	217
PCA 20	185	200	207	213	225
PCA 24	180	194	201	212	221
PCA 30	177	198	205	203	217
KMeans 4	126	132	147	148	147
KMeans 8	124	155	154	155	161
KMeans 12	132	154	158	154	158
KMeans 16	133	154	165	167	173
KMeans 20	132	160	157	159	164
KMeans 24	121	161	153	167	178
Composite 25	**201**	**219**	**230**	**235**	**240**

Table 2: Correctness of Different Feature

5.2 Performance (Problem 2)

Table **??** lists the correctness for different feature. There are 613 queries in total, and the database varies from 1000 images to 5000 images. The table shows that for each test case, how many nearest neighbors are in the same catalogy as the query image.

5.3 The Results (Problem 3)

Figure **??** shows some sample results from both Color Moment HSV 9 features and Composite 25 features. Here are three sample queries. The first, third, and fifth rows in the figure is the results from Composite 25 features, while the second, the forth, and the sixth rows is from Color Moment HSV 9 features. In each row, the first picture is the query, and the following are five best answers according to their relevance to the query. A tick indicates that the answer to its left is correct, i.e., in the same catalogy of the query.

In the first example, the query is a big house. The Composite method finds 4 buildings in the top-5 nearest neighbor searching. The Color Moment HSV method, however, finds many irrelevant pictures. In the second example, the Composite method also finds 4 piano which is the correct. The HSV method fails to find any piano in its 5 nearest neighbor searching process. The thrid example is a waterweel. Both the Composite method and the HSV methods make mistakes in this example, but the Composite method still does better by making three ticks in five answers.

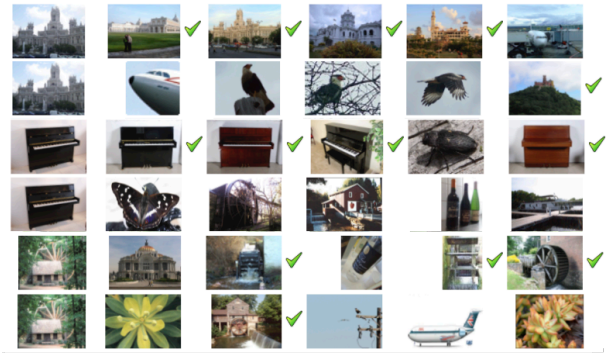


Figure 2: Sample Nearest Neighbors

Function	HSV9	PCA8	PCA16	Composite
$\sqrt{\sum_i (a_i - b_i)^2}$	171	177	205	229
$\sum_i \lvert a_i - b_i \rvert$	179	176	201	237
$\frac{\sum_i a_i b_i}{\lvert\lvert a \rvert\rvert \lvert\lvert b \rvert\rvert}$	167	160	197	232

Table 3: Difference Similarity Functions

Please see `demo.html` under `result.zip` for a more detailed demo.

5.4 Other Similarity Functions (Problem 4c)

We tried two other similarity functions and their comparison with standard Euclidean distance similarity function is shown in table **??**. We can see that under certain feature methods, the absolute difference similarity function (second one) performs better than the Euclidean distance similarity (first one) function. Meanwhile, the cosine similarity (third one) function is worse than two other functions.