Algorithm and Data Structure Coursework: PCA Features 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.

1.1 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 $M^S_{1\ldots3}$ and $M^V_{1\ldots3}$. The final representation is $\mathbb{R}^9$:

$$\left\{ M^H_{1\ldots3}, M^S_{1\ldots3}, M^V_{1\ldots3} \right\}$$

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).

1.2 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.

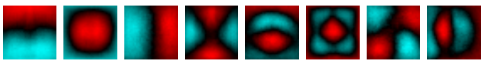
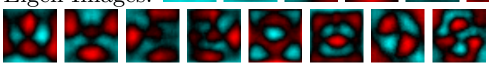
Then, we can use a small set of 32x32 eigen images, as the principle component learned from the dataset, to describe any potential image as close as possible.

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:

Mean: 

Eigen Images: 


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

1.3 K-Means

2. DATA

3. FEATURE FINDING

TODO: list feature here (PCA, KMeans, Composite).

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

Table 1: Node Access Numbers

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 2: Correctness of Different Feature

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 1 lists the node access number in different cases.

TODO: We can see that blablabla

5.2 Performance

Table 2 lists the correctness for different feature. There are 613 queries in total, and the database varies from 1000 images to 5000 images.

6. CONCLUSION

7. REFERENCES

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