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Visual Design of Artificial Intelligence Based on the Image Search Algorithm

Xiaobo Jiang, Zongren Chen*, Jun Yu, and Lixia Huang

Guangdong Polytechnic of Science And Technology, Zhuhai, Guangdong, China
gky7796237@gdit.edu.cn *;
* corresponding author

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Abstract

With the rise of the wave of artificial intelligence and the development and popularization of intelligent technology, the digital images generated by the Internet and mobile intelligence terminals grow exponentially. As the most important information carrier of data content, pictures occupy immeasurable value in this era. To solve the shortage of image search engines, this paper uses the image browsing algorithm, which combines the semantic and image characteristics of the image, and organizes the returned images according to the visual characteristics similarity of the images. In addition, in order to reduce the computational time and improve the performance of similarity search, a near neighbor search algorithm based on key dimensions is applied. Experiments show that the AI visualization design based on the image search algorithm can not only overcome the semantic gap to some extent, but also strengthen the interaction between 88% systems and users to browse the search results more efficiently and naturally.

Keywords: Image Search; Artificial Intelligence; Visual Design; Information Carrier

1. Introduction

In recent years, with the rapid development of computer communication technology, especially the progress of storage technology and the increasing popularity of the Internet, the capacity of information resources all over the world is growing at an amazing rate, which not only have text data, but also contain a large number of multimedia information like sound, images and videos. As an important information carrier, image has rich content and intuitive image, and is an important way to express information. Due to the large amount of image data and rich information, how to better organize, classify and retrieve image data has become a key problem in the field of information retrieval.

AI visualization design based on image search algorithms has attracted the interest of many experts and has been studied by many teams. For example, some teams have found that photo albums developed by the MIT Media Laboratory are an interactive system primarily for browsing and retrieval faces, photo albums include image texture, shape, and face feature retrieval, and the user can select specific feature retrieval accordingly. Some people propose to add facial features to image retrieval and labeling, and the experiments were also completed in the photo album that can help the police quickly identify the offender's facial features [1]. Some teams believe that since the 1990s, institutional scholars at home and abroad have developed a number of content-based image retrieval systems for business or research, these systems usually use and provide the color, textures, shapes of image queries, or with a combination of features, effectively integrate existing image retrieval, database management, human-computer interaction, AI, and other technologies, more notably, the photo albums, QBIC. The MIT Web Search, Columbia University, IBM, Virus Systems at the University of California, Berkeley, Excalibur visual retrieval weapons system, as well as other academic business institutions, laid the foundation for a further study of CBIR [2-3]. Some teams have found that with the development of Internet e-commerce and multimedia technology, the rapid growth from social networks, news websites, mobile phones to multimedia data represented by images brings rich resources, but also suitable for an urgent problem of how to retrieve fast and accurate queries from a large number of multimedia data, especially files with multiple semantics that cannot be directly expressed in text [4]. Even individual teams found that deep learning development, not only used to complete simple image classification tasks, began to use deep learning to do more challenging tasks, such as face recognition, image semantic segmentation, etc., and target detection is the basis of all tasks, the main task is to give the location of the sample image, mark with a rectangular box, and give sample labeling information. The object detection model is able to identify multiple objects in the picture and can locate different objects, so the problem solved by the object detection is the location of the object [5]. According to 2018, WeChat friends uploaded 1 billion; Yahoo Flickr 400 level 400; Facebook app currently over 80000000 photos, over 450 billion since release; in e-commerce giant Alibaba Taobao has stored more than 50 billion images [6-7]. Although their research results are all very rich, there are still some shortcomings.

Although the current computer has made great progress in understanding the underlying semantic information and the content of the top semantic image information, it is still difficult to fully accurately understand the semantics of the image, with a certain semantic gap, so the expression and modeling interested in the image letters has always been a difficult and hot spot, so this paper introduces the design of artificial intelligence visualization, based on the image search algorithm.

2. Methodology

2.1. Similarity Measure

High-dimensional databases mainly measure the similarity of these two objects through the distance between objects, so, similarity measurement is a very important topic in high-dimensional query processing, here are some of the more commonly used distance formulas [8]. The Minkowsky distance is:

$$d(X,Y) = \left[\sum_{i-1}^{n}\left|x_i - y_i\right|^{\lambda}\right]^{\frac{1}{\lambda}} (1 \leq \lambda\infty) \tag{1}$$

When λ =1, formula (2) is the Manhattan distance,

$$d(X,Y) = \sum_{i-1}^{n}\left|x_i - y_i\right| \tag{2}$$

When λ =2, formula (3) is the Euclidean distance,

$$d(X,Y) = \left[\sum_{i-1}^{n}\left|x_i - y_i\right|^{2}\right]^{\frac{1}{2}} \tag{3}$$

When the λ = ∞, formula (4) is the Maximum distance,

$$d(X,Y) = max\left(\left|x_i - y_i\right|\right) \tag{4}$$

The Manhattan distance based query corresponds in a geometric sense to hypercubes, the maximum distance based query is the super diamond, and our most commonly used one is the Euclidean distance, whose query corresponds to the hypersphere [9].

2.2. Similarity Query

The query of high-dimensional data is usually similarity query, similarity query includes the following common ways: point query, point query is the simplest type of query, for the database of DB, query point q, similarity measure m, its query expression is formula (5), point query and traditional precision query are similar to [10].

$$Point\ Query(DB, q, m) = \{p \in DB\ /p = q\} \tag{5}$$

2.3. Concepts of the Principal Component

Assuming the p dimension vector, there are obviously many ways to synthesize p variables into one variable for xp,x2,x1,respectively, and the simplest and direct method is the linear combination, as shown in formula(6).

$$y = \alpha^T x = \alpha_1 x_1 + \alpha_2 x_2 + ... + \alpha_p x_p \tag{6}$$

Obviously, there are different combinations of the coefficients of different variables, obtaining different integral quantities, and in order to achieve dimensionality reduction, we naturally want to construct some such integrals in place of the original variables. In order to avoid the information overlap between the constructed integrated quantities, the integrated amount needed to be constructed is not interrelated, and the integrated quantity can reflect the change of the original variable to some extent, including the maximum change of the original variable, called the first main component reflecting the change of the original variable and other [11].

2.4. Effectiveness Based on Main Component Filtering

The filtering of the main component is based on the distance scale, triangle inequalities and the variance statistical characteristics of the main component. Through the preliminary screening of the main component, it can both retain all the correct query results and avoid some distance calculation, saving the time of the similarity query.Theorem 1: set V={p1, p2, …, pm}is a set of eigenvectors in n dimension, p is any eigenvector in set V, if query vector is a point where q,query radius is r, to q distance less than r, then each dimension must be within the r neighborhood of q, as shown in formula (7).

$$d(p, q) = \sqrt{\left(\left(p_1 - q_1\right)^2 = \left(p_2 - q_2\right) + ... + \left(p_k - q_k\right) + ... + \left(p_n - q_n\right)^n\right)} \leq r \tag{7}$$

Evidence: eigenvector s, in point set V, its distance to q is less than r. The proposition holds, assuming that the projection of s in dimension k is not within the r neighborhood of q, and that |sk−qk|>r, has (sk−qk)2>r2 against the question from this d(s,q)>r.

3. Experiments

3.1. Experimental Data Sources

The AI visualization design based on the image search algorithm developed in this paper is a content based image search operated through convolutional neural network models to extract abstract semantic features capable of describing global and high-level image content. Based on the research status of high-dimensional data index structure, the statistical features of P2-tree.

3.2. Experimental Design

The P2-tree algorithm first analyzes the main components of the data set, then divides the data set and establishes the index tree; and filters the data space using the triangle inequality property and the main components. It is shown theoretically and experimentally that the proposed algorithm can effectively reduce the number of distance computations, have good similarity query performance, and somewhat overcome the dimensionality crisis.

4. Result

4.1. Analysis the Corel5k Dataset

In Table 1, the method assumes image sampling as hsv(128*128) and is compared to other classification algorithms in the table (with 30 training images for each category). The proposed method is to transform the diverse present problem into the traditional singleton case, which can also effectively avoid the local minimization points and obtain the optimal image classification performance. As described in the above table, the P value (i. e., the website) =0.000 is less than 0.05, indicating a good level of reliability in the questionnaire.

Table 1. Performance comparison of different multiple sample algorithms on the Corel5k dataset

MIL algorithm	**EM DD**	**Iterated discrim APR**	**Citation - KNN**	**Mi SVM**	**This algorithm of this algorithm**
Field	0.752	0.811	0.765	0.835	0.822
Lake	0.638	0.645	0.635	0.755	0.782
Mountain	0.627	0.594	0.640	0.725	0.772
Sunset	0.766	0.796	0.882	0.927	0.931
Waterfall	0.650	0.642	0.687	0.822	0.791
Average	0.687	0.711	0.735	0.812	0.819

4.2. Analysis the Subset of Flickr Data

Figure 1 mainly shows the functional relationship between the search error rate and several different algorithms of parameter ε. It can be seen from the graph that the error rate of this method is far lower than L2-based LSH distance and L2 Euro-style distance-based linear search, similar to HML-based linear search. Figure 1 mainly represents the functional relationship between the search database and the parameter ε, which apparently controls the required retrieval time.

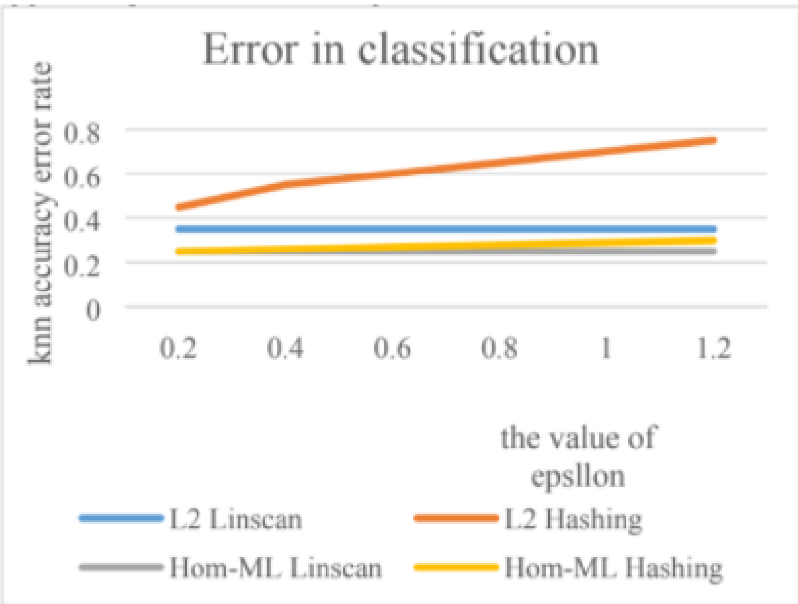

Figure. 1. The algorithm classification error corresponding to different values on the Flickr dataset

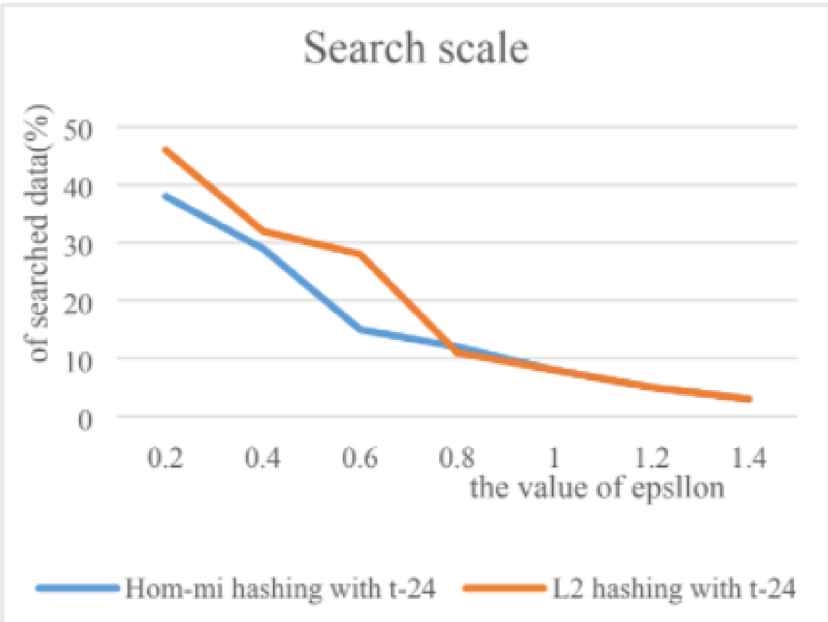

Figure. 2. The algorithm search ratio corresponding to different values on the Flickr dataset

As can be seen from Figure 2, the present method is lower under the same ε value than the ordinary LSH algorithm based on L2 European distance. Experiments demonstrate that when retrieving a small number of databases, the semi-supervised hash method proposed in this section achieves higher accuracy, with a retrieval time of about 1.7 seconds per query image, a about 12.8% improvement than the 1.95 seconds of the LSH algorithm.

4.3. Analysis the MNIST Dataset

Convolutional neural networks have always been one of the best performing methods in handwriting digital recognition, and Table 2 shows the error rate comparison of this section with various other unsupervised and supervised sparse coding and supervised convolutional methods for convolutional neural networks on MINST. In experiments, the number of hash coding bits is set to 48 bits and the soft maximum output classification to 10 classes, the proposed method outperforms supervised CNN, and achieves good results in classification accuracy evaluation. In particular, the algorithm greatly reduces the error rate compared to single-layer sparse coding and standard sparse coding several years ago, and compared to the same hierarchical sparse coding approach, considering that the algorithm mainly focuses on designing the retrieval architecture rather than single classification tasks, therefore, the algorithm architecture is feasible when the accuracy is slightly lower.

Table 2. Error performance comparison of (%) on MNIST based on each pixel-level sparse coding algorithm

Method	Error rate(%)
Standard sparse encoding	2.10
Scalable LCC(Unsupervised) [233]	1.64
Differentiate sparse encoding (supervised) [234]	1.30
Super Supervised sparse coding [235]	1.05
Single-layer sparse encoding (unsupervised) [218]	0.98
CNN(is supervised) [236]	0.82
Leveler-level sparse encoding of the + SVM[220]	0.77
measure	0.797

Table 2 results show that embedding compact hashing coding in this method has little effect on the accuracy of the final classification.

4.4. Experiments and Analysis of the Close-neighbor Search Algorithm

The first 1000 retrieved images are selected, first, the 72-dimensional feature vectors of each auxiliary image are calculated, and then the nearest neighbor is calculated according to the algorithm proposed here, pair vector set algorithm, one by one comparison method and M-tree algorithm. The performance of the proposed algorithm is mainly measured mainly by the number of node distances calculated in Figure3, using the nearest neighbor search algorithm to reduce the distance between two points one by one, thus shortening the search time.

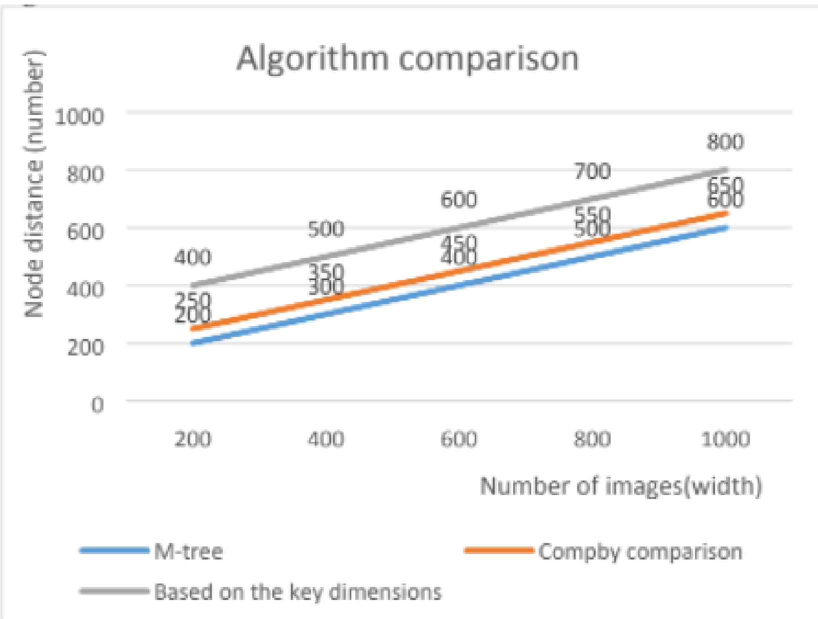

Figure. 3. Algorithm comparison

Controlled by Figure3, the M-tree algorithm has no advantages on small datasets, the computation between nodes is greater than the number of node sets, and has better performance over the one-by one comparison method.

5. Conclusion

The content-based image retrieval system mainly extracts the feature vectors from the image, and then uses the feature vectors for matching, searching and automatic feature extraction by computer, overcoming the inefficiency and multiple significance of manual annotation. This paper studies two key techniques in image retrieval: high-dimensional index and organization and browsing of retrieval results. After extracting feature vectors from an image, the similarity between images changes to eigenvector and image search to eigenvector query. However, for sequential scanning, the distance between computing vectors requires considerable CPU time and input / output cost, so, when the database is high, the similarity query of the sequential scanning leads to slow response speed and cannot meet the real-time requirements of image retrieval, so an effective index structure is needed to accelerate the execution of the query, where both principal component analysis and cluster analysis can effectively improve the performance of the index structure. Currently, WWW image search engines have many deficiencies in the expression of search results and the interaction with users, which, under existing search models, can help users find the information they need faster and improve their search efficiency.

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