Fast Retrieval Method of Image Data Based on Learning to Hash

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Abstract. Hash is a method that is widely used in nearest neighbor retrieval, and its goal is to convert high-dimensional image data into low-dimensional representations or into a set of ordered binary code. As one of the more efficient methods of data storage and retrieval, the hash method is widely used in the nearest neighbor retrieval of large-scale image data. The traditional hashing method generates a hash code by manually extracting features, so that the feature and the hash code do not have the best fit, so that the generated hash code is suboptimal. The rapid development of deep learning makes the computer have a good effect on image visual feature recognition. Combining the learning of hash function makes the performance better than the traditional hash method. In this paper, a deep hash method based on triple constraint is proposed to extract the similarity features of the same category and distinguish the features between different categories. Further learning the hash code makes the similarity of the image preserved. Experiments show that the Hash-based learning method has better performance on CIFAR-10 and NUS-WIDE than other methods.

1. Introduction
With the rapid development of Internet in recent years, high-dimensional data grow exponentially and their use is brought to center stage of all fields. In the past, relevant researchers put forward many methods of data retrieval. Among these methods, hash is widely used for its highly efficiency in storage and computing [1]. Traditional hash method that includes locality sensitive hash and spectral hash has made some achievements in image retrieval, but it has a long way to go before practical application. The rapid development of deep learning contributes to the improvement of hash method. In 2014, Pan and Yan firstly proposed Convolutional Neural Network Hashing CNNH [2] after being combined with Convolutional Neural Network. Compared to traditional hash method, the new proposal has better performance. CNNH has two stages to train hash codes: first, decompose similar matrix S into multiplication of HT and H, and every matrix element represents that whether its sample image are similar in line and row. Every line of matrix H is similar hash codes for training data. The image features in the process of training can’t react on generating hash codes and adjust hamming distance between hash codes dynamically. Therefore, the advantage of Convolutional Neural Network can’t be utilized so as to make the hash function suboptimal. Based on that, this paper put forward Deep Neural Network Hashing [3] and Deep Supervised Hashing [4] consecutively. These two models adopt end-to-end model to essentially overcome the problem of separation between CNNH feature
extraction and hash coding, and design loss function from different angles for generating hash codes. However, frequent relaxation in generating hash codes will cause deviation of negative feedback in the mode training. In order to overcome the defect, the research project proposed Structure of Deep Hash Network based on triplet constraint.

2. Model of Deep Hash Based on Triplet

According to research, CNN is superior than the manual extraction in image feature extraction and can efficiently extract the similar features between the samples of the same class in feature extraction. Therefore, this research project put forward the Network Structure of Learning to Hash Based on CNN Extraction Feature, and relevant verification has been done. In this network structure, phased training replaced end-to-end training, which means high-dimensional image data generate hash code directly. Even though with superior features, end-to-end training has a disadvantage of over relaxation because the hamming distance of binary hash code is discrete and non-differentiable that will affect the model image feature extraction. Therefore, the training is divided into two phases. In the first phase, one dimensional feature vector represents sample image through feature extraction layer, \( L \) is the length of the finally generated hash codes, \( n \) is natural number. In the second phase, output feature vector as hash codes with the length of \( L \) through hash layer. Structure of deep hash network is shown in figure 1.

![Figure 1. Structure of deep hash network.](image)

2.1. Model Input

Deep Hash Network Learning belongs to supervised learning and inputs training data with tags. The training data of this model are a series of dataset with tags \( \{(p_1, w_1), (p_2, w_2), (p_3, w_3), \ldots (p_n, w_n)\} \) , among which \( p_i \) is sample image, \( w_i \) is the tag of corresponding sample image. Triplet constraint is the contiguous relations among samples \( \{p_i, p_j, p_k\} \). The distance between \( p_i \) and \( p_j \) is shorter than that between \( p_i \) and \( p_k \) with certain measurement method. Compared to label constraint and pairwise constraint, triplet constraint is weaker in constraint but superior in categorizing and adapting to model in practical training. Among the triplet tags input, \( p_i \) and \( p_j \) are of the same category, \( p_i \) and \( p_k \) are of different categories. The similarity distance between the same category is shorter than that between different categories.

Generally speaking, all the training data are combined. If the number of training sample images is \( N \), the number of combined samples is \( O(N^4) \), which is inefficient to model training. The error among the training samples will misguide the generation of models. To ensure that the model can fast converge to triplet constraint condition, smaller scale of data is used to train model online in a large scale. For example, 40 small-scale sample images are chosen to establish triples. This method can renew model parameter with every batch of samples to avoid overfitting. The establishment of smaller scale triples should obey rules as follows: (1) ascertain the number of samples with different tags and choose fewest ones; (2) randomly reshuffle certain tag and choose \( i \) and \( i+1 \) as anchor \( p_i \) and positive example \( p_i \) in the triples respectively; (3) randomly choose any other samples with tag \( i \) as negative
example $p_t$ of triples $p_i$ (4) circulating all tags and samples to generate a random combination with anchor, positive example and negative example. With the aid of these rules, uniform distribution of sample data is guaranteed to increase randomness.

2.2. Model Structure

Deep Hash Model based on Triples consist of two modules-Feature Extraction Module and Hash Module. Feature Extraction Module uses general structure of network similar to AlexNet [5], including 5 Convolutional layers and 2 Fully Connected layers. The output layer is feature vector with certain length. Then the feature vector in the interlayer maps to hash code through hash layer. Hash layer consists of 2 Fully Connected layers and Activation Function layer. The incidence relations among features are extracted through further learning to narrow the hamming distance among corresponding hash codes with shorter feature distance.

Feature Extraction module’s main aim is to extract feature to make relations among training data preserved in feature layer. As to the network structure, this paper uses AlexNet-similar structure. Generally, this structure includes 5 convolutional layers, 2 Fully Connected layers and 1 Output Feature layer. Specific parameters are shown in table 1.

### Table 1. Model parameter.

| Layer | Input | Convolution kernel /number | Output | Activation function |
|-------|-------|-----------------------------|--------|--------------------|
| Con_1 | $227 \times 227 \times 3$ | $11 \times 11 \times 3/96$ | $55 \times 55 \times 96$ | Relu |
| Pool_1 | $55 \times 55 \times 96$ | $3 \times 3 \times 1/1$ | $27 \times 27 \times 96$ | - |
| Con_2 | $27 \times 27 \times 96$ | $5 \times 5 \times 96/256$ | $27 \times 27 \times 256$ | Relu |
| Pool_2 | $27 \times 27 \times 256$ | $3 \times 3 \times 1/1$ | $13 \times 13 \times 256$ | - |
| Con_3 | $13 \times 13 \times 256$ | $3 \times 3 \times 256/384$ | $13 \times 13 \times 384$ | Relu |
| Con_4 | $13 \times 13 \times 384$ | $3 \times 3 \times 384/384$ | $13 \times 13 \times 384$ | Relu |
| Con_5 | $13 \times 13 \times 384$ | $3 \times 3 \times 384/256$ | $13 \times 13 \times 256$ | Relu |
| Pool_5 | $13 \times 13 \times 256$ | $3 \times 3 \times 1/256$ | $6 \times 6256$ | - |
| Full_6 | $6 \times 6 \times 256$ | - | $4 \times 096$ | Relu |
| Full_7 | $4096$ | - | $4096$ | Relu |
|Feat_8 | $4096$ | - | $n \times L$ | - |
|Hash_9 | $500$ | - | $500$ | Relu |
|Out | $500$ | - | $L$ | Tanh |

The main function of hash module is to output the inter feature layer to hash code through hash layer. Each fully connected layer consists of single layer 500×1 neuron and activation function. The function of fully connected layer is to connect every feature in the inter feature layer, extract the relation among features and make the relation correspond to different bits of hash code through hash module, thus making different sample images generate hash codes with longer hamming distance. Certain image feature and some image features will be reflected on the bits of hash code.

2.3. Loss Function

2.3.1. Feature Extraction Layer. The convergence condition of deep hash network is that the output of feature vector by training data in the feature vector layer satisfy triplet constraint condition. This condition enables the feature extraction module to extract more performative features. Triplet constraint applied to feature extraction module in this model means the Euclidean distance between feature vectors of the same category is shorter than that between feature vector of different categories. The equation is as follows:
\[ \text{Loss}_\text{triplet} = \sum_i \left( \| f(x_i^a) - f(x_i^p) \|_2 - \| f(x_i^a) - f(x_i^n) \|_2 + \text{threshold} \right) \]  

(1)

In this equation, \( x_i^a \) signifies anchor sample, \( x_i^p \) signifies positive example sample, \( x_i^n \) signifies negative example sample, \( f \) is mapping function through learning (mapping the sample from sample image to feature vector), \( \text{threshold} \) signifies certain threshold used to control the distance between positive example and negative example. \( \| \cdot \| \) signifies the Euclidean distance between feature vectors. In equation (1), the error satisfying that in-cluster-distance is shorter than between-cluster-distance is 0, otherwise it means there is error using “+” as signifier in the equation.

In the training phase, smaller the value of \( \text{threshold} \) is, easier the loss function \( \text{Loss}_\text{triplet} \) is to tend to 0; the distance between anchor and positive example is not too short, and the distance between anchor and negative example is not too long. However, the model is hard to converge. When the value of \( \text{threshold} \) is larger, the model will make the distance between anchor and positive example shorter, and between anchor and negative example longer, as well as make the loss function \( \text{Loss}_\text{triplet} \) remain a large value. Therefore, a reasonable \( \text{threshold} \) value is essential to model training. Deep Hash Network uses triple loss function to constraint in the feature extraction layer, that is making negative feedback network and modifying network parameters to get more performative features through minimizing \( \text{Loss}_\text{triplet} \).

2.3.2. Hash Layer. In the hash layer, pairwise constraint acts as constraint condition, and feature vector in inter feature layer is input in this phase. \( w_i=1 \) signifies that the samples represented by two feature vectors are of the same category, and \( w_i=0 \) means that the samples represented by two feature vectors are of different categories. When the feature vector \( F_i, F_j \in R^m \) generated by feature layer is mapped to hash space to be output as \( bi,bj \in \{-1,1\}^m \), \( \text{dist}_H(b_i,b_j) \) is the hamming distance between \( bi,bj \). The loss function designed is as follows

\[ \text{Loss}_\text{pair} (b_i, b_j, w_i) = \frac{1}{m}(w_i \cdot \text{dist}_H(b_i,b_j) + (1-w_i)[m-\text{dist}_H(b_i,b_j)]) \]  

(2)

The pairwise constraint \( \{ p_i, p_j, w_i \} \) is input into hash model. When \( w_i=1 \), derivation and gradient descent of \( \text{Loss}_\text{pair} \) will shorten the hamming distance between \( bi \) and \( bj \) as soon as possible and decrease the value of \( \text{Loss}_\text{pair} \). When \( w_i=0 \), the hamming distance between \( bi \) and \( bj \) will be lengthened. When the loss function acts as constraint condition, the hamming distance between hash codes generated by samples of the same category is shorter, and that of different categories is longer. In this way, the hash codes are optimal.

In equation (2), the function \( \text{dist}_H(b_i,b_j) \) is discretized. Because its gradient is indifferentiable, traditional way can’t be used to do random gradient descent, that is back-adjusting of model parameter can’t be done. In order to solve the problem that loss function is indifferentiable, the generating of hash codes need to be reconsidered. The feature vector of sample image is resulted from \( \tanh \) function after the hash layer and before the generating of hash code. The \( \tanh \) function can compress the real number value within (-1,1); when the value is around 0, the gradient value is higher; that the value is around -1 and 1 is advantageous to the generating of hash codes. In the process, it is known that the final hash codes are the final \( bi \) and \( bj \) only after slack variable. Before that, the value is \( u_i \) and \( u_i, u_j \in R^m, u_i \in R^m \). In order to make the function derivable during the training, hash codes \( bi \) and \( bj \) are replaced by prerelaxation variate \( u_i \) and \( u_j \) when calculating loss function. In an effort to prevent the model from overfitting and improving generalization during the training, regular terms are added after loss function. The loss function in practical training is:

\[ \text{Loss}_\text{relax} (u_i, u_j, w_i) = \frac{1}{m}(w_i \cdot \text{dist}_H(u_i,u_j) + (1-w_i)[m-\text{dist}_H(u_i,u_j)] + \alpha(|1-|u_i|_1| + |1-|u_j|_1|)) \]  

(3)
In this equation, $\alpha$ is preference norm weight. When $\alpha \to 0$, the model tends to be overfitting, and when $\alpha \to \infty$, the model tends to be underfitting. Therefore, appropriate value of $\alpha$ is important to the model training as well.

3. Rearrangement Algorithm of Hash Code Based on Feature Weight

3.1. Definition of Feature Weight

The hash function generated in the deep hash model enables every sample image in sample database to have the personalized hash code $\{h_i, h_2, \cdots, h_m\}, h_i \in \{0,1\}$. The form of the hash code is different from that in section 1; thus $h$ is used to symbolize the hash code. When sample q’s similar image is to be searched, the calculation equation of hamming distance between sample q and images in sample database is as follows:

$$dist_H(h_i, h_q) = \sum_{k=1}^{m} (|h_{i,k} - h_{q,k}|)$$

(4)

In this equation, $dist_H(h_i, h_q)$ is hamming space, $m$ is the length of hash code. It is known from the equation that the function of every bit of hash codes is same. Besides, every bit of hash codes is the combined performance of single feature or multiple features in generating hash codes, which is often neglected when hamming distance is used to search. Except that the features can’t be performed, in the researching of images, the search results of the same hamming distance can’t be further categorized so as to make the research results unspecific. In that condition, every hash code can be given a specific special weight $\omega_j$, and weighted hamming distance is used to calculate hamming distance. Besides, the similarity between query sample and sample database can be further refined. That will make the return results have higher similarity with query sample. In the experiment, every hash code can be given a specific weight. If the weight of certain category of hash codes is $\omega=\{\omega_1, \omega_2, \omega_3, \cdots, \omega_m\}$, then hamming distance is:

$$\overline{dist}_H(h_i, h_q) = \sum_{k=1}^{m} (\omega_k |h_{i,k} - h_{q,k}|)$$

(5)

Compared to discrete hamming distance, weighted hamming distance that has smaller similarity metering granularity will further categorize the same hamming distance. There are various ways of weighting hamming distance. This paper put forward to a new one. For every bit’s weight, detailed introduction to the design will be done later.

3.2. The Design of Feature Weight

Image research mainly studies on the approximate nearest neighbor search in Euclidean space. A set of data point $\{x_i \mid i = 1, 2, 3, \cdots, n\}$ and a search data point $q$ are given, and all data points satisfying $\|q - x_i\|_2 < \epsilon$ are returned. In recent years, more and more researchers have been using hash codes as highly efficient algorithm for image searching. The idea of nearest neighbor search in Euclidean space can be applied into hash space. Given that the image data $pi$ in the sample database responds to hash codes $\{h_{i,1}, h_{i,2}, h_{i,3}, \cdots, h_{i,m}\}$, query sample is $p_{query}$, $\{h_{query,1}, h_{query,2}, h_{query,3}, \cdots, h_{query,m}\}$, then in hamming space, the query image’s $\epsilon$ neighbor can be expressed as equation (6).

$$NN(p_{query}, \epsilon) = \{p \mid \|p_{query} - p\|_2 < \epsilon\}$$

(6)

The simpleness and efficiency of hamming distance should be retained in the design of hamming distance weight. The feature weight is put forward to in this paper based on hamming space $\epsilon$’s
neighbor. Before the calculation of weighed hamming distance, \( \varepsilon \) ’s neighbor sample collection \( p \) should be retrieved through hamming distance. The hamming distance between all samples’ hash codes and query sample’s hash codes should be shorter than \( \varepsilon \) in the collection \( p \), and hash codes are different, which can be illustrated in figure 2. The way to define the weight of different bit hash codes is like this: first, the statistics of all samples in collection \( p \), including the probability of being “0” or “1” for every bit; second, the calculation of weighed hamming distance in query samples and sample database in this sample collection in the method of probability.

![Figure 2. Hamming space \( \varepsilon \) neighbor.](image)

For all the hash codes generated by the sample data in this collection, given that \( P("1") \), is the probability of the hash code’s \( i \) bit as 1, given \( P("0") \), is the probability of the hash code’s \( i \) bit as 0, then relation equation is as follows:

\[
P("1")_i + P("0")_i = 1
\]

(7)

From the equation, the features in sample \( p \) aggregate in a obvious way. Most hash codes in the sample tend to be definite in certain bit. For example, sample cats are mainly differentiated through the “cats”, so the cats data with ears in the sample database will be highly consistent with each other in certain bit. The bit is more important than others in weight design, and the weight will be renewed according to the importance when the hash code bit’s weight is calculated.

The calculation of weight \( \omega \) is illustrated in algorithm 1.

**Algorithm 1.** The calculation of weighted vector \( \omega \)

| input: All hash codes \( p \) generated by image sample database, the hash codes \( p_{query} \) for querying data, the value of \( \varepsilon \) for querying \( \varepsilon \) neighbor |
| output: Samples of this category \( \omega = \{\omega_1, \omega_2, \omega_3, \cdots, \omega_m\} \) |
| (1) Returns query sample’s \( \varepsilon \) neighbor collection \( p \) through \( \| p_{query} - p \| < \varepsilon \) |
| (2) The statistics of bits with high probability of being “0” or “1” for all hash codes in sample collection \( p: S = \{S_1, S_2, S_3, \cdots, S_m\}, S_i \in \{0,1\} \) |
| (3) The probability of every bits of hash code being “1” in nearest neighbor query sample collection \( p \) \( P(S_{i,1}) = \{P(S_{i,1}), P(S_{i,2}), P(S_{i,3}), \cdots, P(S_{i,m})\} \), among which the calculation of \( P(S_{i,1}) \in [0,1], P(S_{i,2}) \in [0,1] \) is \( P(S_{i,1}) = \sum(S_i = 1, NN(p_{query}, \varepsilon)) / count(NN(p_{query}, \varepsilon)) \), count is the quantity satisfying the conditions. |
| (4) for \( i = 1 \) to \( m \) |
| (5) \( \omega_i = 1 + \max(P(S_{i,0}), P(S_{i,1})) / m \) |
| (6) \( i++ \) |
| (7) End |
| (8) output \( \omega = \{\omega_1, \omega_2, \omega_3, \cdots, \omega_m\} \) |
From the calculation method of weighted $\omega$, it is known that the weighted is to differentiate the samples with the same hamming distance, which basically retain the relationship between hamming distance and similarity. The relationship between hamming distance and weighed hamming distance is as follows:

$$
\hat{dist}_{H} (h_i, h_q) \leq dist_{H} (h_i, h_q) \leq \hat{dist}_{H} (h_i, h_q) + 1
$$

(8)

In this equation, $\hat{dist}_{H} (h_i, h_q)$ is weighted hamming distance. On the basis of keeping high efficiency, weighed hamming distance further thin the category rules and solve same hamming distance’s sequence problem. The output after reset has better effect compared to hamming distance’s direct output.

4. Experiment and Result Analysis

4.1. Hash Network Experimental Result

In the dataset experiment of CIFAR-10 [6] and NUS-WIDE [7], 600 image samples are extracted from every category of the CIFAR-10 dataset as the experiment data, 500 as training data, other 100 as measurement data, in order to guarantee the efficiency and reliability of experimental comparison. Because NUS-WIDE dataset is multi-tag, two image samples with the same tag are regarded as of the same category of sample data. In this experiment, calculation method is the same as others and mPA of top 5000 return samples is the final comparison datum. The result shows that FastH, CNNH and NINH [8] combined with deep neural network have higher precision compared to traditional ways. In CNNH, the hash codes for overfitting through deep neural network is suboptimal compared to that from other hash learning. The comparison experiment shows that deep hash put forward in the project has better experimental effect. Data measurement standard mAP becomes higher with increasing hash code length. Shown in table 2, deep hash model put forward in this paper has improved to some extents compared to other ways. It is especially obvious when compared to such traditional hash ways as LSH [9], SH [10] and ITQ [11]. FastH, CNNH and NINH have improved in CIFAR-10 dataset and NUS-WIDE dataset, which verifies deep hash model’s excellent performance in hash coding.

Table 2. Dataset retrieval accuracy (mAP) results comparison.

| Method | CIFAR-10 (mAP) | NUS-WIDE (mAP) |
|--------|----------------|----------------|
|        | 12 bit | 24 bit | 32 bit | 48 bit | 12 bit | 24 bit | 32 bit | 48 bit |
| Ours   | 0.573  | 0.586  | 0.607  | 0.611  | 0.708  | 0.745  | 0.752  | 0.764  |
| NINH   | 0.552  | 0.566  | 0.578  | 0.581  | 0.674  | 0.697  | 0.713  | 0.715  |
| CNNH   | 0.439  | 0.476  | 0.472  | 0.489  | 0.611  | 0.618  | 0.625  | 0.608  |
| FastH  | 0.305  | 0.349  | 0.369  | 0.384  | 0.621  | 0.650  | 0.665  | 0.687  |
| SDH    | 0.285  | 0.329  | 0.341  | 0.356  | 0.568  | 0.600  | 0.608  | 0.637  |
| KSH    | 0.303  | 0.337  | 0.346  | 0.356  | 0.556  | 0.572  | 0.581  | 0.588  |
| LFH    | 0.176  | 0.231  | 0.211  | 0.253  | 0.571  | 0.568  | 0.568  | 0.585  |
| SPLH   | 0.171  | 0.173  | 0.178  | 0.184  | 0.568  | 0.589  | 0.597  | 0.601  |
| ITQ    | 0.162  | 0.169  | 0.172  | 0.175  | 0.452  | 0.468  | 0.472  | 0.477  |
| SH     | 0.127  | 0.128  | 0.126  | 0.129  | 0.454  | 0.406  | 0.405  | 0.400  |

Deep hash network model experimental comparison shows that CIFAR-10 improved obviously in data integration and the improvement rate for different bite hash codes are 3.8%, 3.5%, 5.0% and 5.1% respectively. In NUS-WIDE dataset, the improvement rate for different bit hash codes are 5%, 6.8%.
5.4% and 6.8% respectively. The experimental comparison concludes that improvement at different degree has been made in hash codes with different lengths in different dataset.

In this project research, hash codes are generated through two stages. Image features are extracted through feature extraction and triple loss function. In this experiment, the features length is also an essential factor to influence hash codes generation. Shorter feature is more likely to overfit in hash layer, while longer feature will extract interference feature and influence the generation of hash codes. In order to get the value of optimal feature layer length, this paper compares different feature lengths’ influences on the final mAP results. The length in the experiment is connected with the final generated hash codes. The author compares L, “2*L”, “3*L”, “4*L” and “5*L”, and ‘L’ is the final hash length. The broken lines in comparison figure stand for the hash codes with different lengths NUS-WIDE (figures 3 and 4).

The author compares L, “2*L”, “3*L”, “4*L” and “5*L”, and ‘L’ is the final hash length. The broken lines in comparison figure stand for the hash codes with different lengths NUS-WIDE (figures 3 and 4).

Through analyzing the broken lines of these two datasets, this paper finds that when the feature layer length is the same as the length of hash codes, the hash codes can be directly generated through disposing in this layer, but the result is not so optimal. With the increase of feature layer length, the result is optimal as feature layer length is four times of that of the hash codes. When the feature layer length is increasing, the mAP of partial data will decrease mildly. Therefore, the feature layer length chosen in table 2 is “4*L”, which is the optimal feature layer length in this experiment by measurement.

In the visual experiment, image retrieval is done mainly through CIFAR-10 dataset (figure 5). This dataset is single tag dataset. As every sample image in the dataset is loaded with less information, it can standby certain feature more accurately. The advantage is beneficial to a more intuitionistic display of retrieval return result. The experimental principle is that: first, return TOP-K samples whose hamming distance with retrieval sample hash codes is the shortest; second, return 10 samples images whose hamming distance with retrieval sample in the first place of every row is the shortest. From the returned sample image, it is shown that the features extracted by deep hash network model have different categories. The result of image retrieval depending on hash based on deep hash network model has higher precision from the perspective of object category; from subject perspective, the similarity between returned result and retrieval samples is not optimal. The retrieval image is partial to be the sample of the same category theoretically.

4.2. Rearrangement Algorithm Experiment
This experiment mainly aims to compare and verify deep hash return result rearrangement.

The first step is to generate responding hash codes of CIFAR-10 dataset deep hash network model based on triples; then return retrieval results based on feature weight rearrangement algorithm. There
is a key parameter $\epsilon$ in this experiment which means the hamming distance is shorter than $\epsilon$ in hamming space. $\epsilon = 2$ represents that when the hamming distance is shorter than 2, rearrangement algorithm based on feature weight is used to rearrange and return the return results. Illustrated in figure 6, the result after rearrangement from the perspective of visualization has the same features with retrieval samples, and it is more reasonable to be as return result. Rearrangement algorithm can differentiate the return results with hamming distance and different hash codes. This paper found that the return results keep the same before rearrangement and after rearrangement. The comparison between direct return TOP-K result by hamming distance and the return result after rearrangement shows the numbers of samples of the same category in the top 10 return results increases, which symbolizes a higher precision. It also shows a higher similarity in subject visual. Shown in figure 6.

Figure 5. Visual experiment.

Figure 6. Rearrangement algorithm visualization experiment.

The precision of different K value’s return results changes after subject judgement is made. The comparison of different K values’ accuracy can make rules summarized. The smaller of TOP-K K
values are, the higher precision is after rearrangement. With K values increasing, the precision gap after and before rearrangement is shortening until to 0. It is verified that hash rearrangement algorithm based on quantification can differentiate the same hash codes’ return results and compare retrieval samples’ similarity. The change of precision is illustrated in figure 7.

![Figure 7. Accuracy of 24bit.](image)

5. Conclusion

This paper completes the structure of deep hash network and does comparative experiment of rearrangement algorithm. The result verifies that structure of deep hash network has better performance, and rearrangement algorithm has better visual effect on image retrieval based hash codes. In previous research of hash function, the similarity comparison was done through the comparison of hamming distance; while hamming distance’s index of discrimination isn’t satisfactory for larger scale of data. This paper uses hash codes as index and further distinguishes the similarity of return results with the same hamming distance so as to get return results with higher similarity. The method put forward in this paper has improved to some extents compared to other methods, but has a long way to go before being free from any defects. The experiment only focuses on dataset. Therefore, the author will continue to learn relevant professional knowledge to make hash-based retrieval method applied to practical retrieval system and improve data utilization ratio.

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