# Intelligent Detection and Search Model for Communication Signals Based on Deep-Re-Hash Retrieval Technology

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***Abstract*—With the explosive growth of image data, traditional image retrieval methods face challenges of low efficiency and insufficient accuracy. In view of this, the study first analyzed the traditional Deep-Re-Hash detection technology and constructed a general hash detection model. Secondly, Cauchy functions and Hadamard matrices were introduced to optimize the generation of hash centers, and an improved Deep-Re-Hash detection model was proposed. The experimental results showed that the highest precision of the improved Deep-Re-Hash was 97%, and the highest MAP value was 90%. In simulation testing, the lowest detection similarity of the improved Deep-Re-Hash detection model was 64.8%, and the detection speed at this time was 7.6s. The hash codes generated by this model were highly aggregated, with very clear edges. In the indicator rating, the highest storage occupancy rating was close to 45 points, the highest detection satisfaction rating was close to 50 points, and the highest detection time rating was close to 30 points. Based on the above data, the proposed improved Deep-Re-Hash detection model shows great potential in processing large-scale image data. It successfully improves the intelligent detection and search efficiency of communication image signals, providing useful reference and inspiration for researchers in related fields.**

***Keywords*—Deep-Re-Hash retrieval; communication signals; image data; cauchy function; hadamard matrix**

## I. Introduction

In modern communication systems, the transmission and storage of image signals is an important field. With the explosive growth of image data, it is important to efficiently detect and search for image signals [1]. Traditional image retrieval methods face challenges of low efficiency and insufficient accuracy. To address these challenges, deep learning technology has emerged in recent years. Its outstanding feature learning ability and highly non-linear processing ability have achieved significant success in image signal processing [2]. However, when faced with large-scale image signal datasets, traditional methods still face enormous pressure on storage and computing resources. To overcome these challenges, Deep-Re-Hash (DRH) retrieval technology has emerged [3]. DRH maps images into compact binary encoding, enabling efficient image retrieval and search. This method has broad application potential in Communication Image Signal (CIS) processing. By learning the hash code of images, it is possible to compare images in low-dimensional binary space and perform high-speed similarity search [4]. To further optimize the practical application performance of this technology, the algorithm structure was innovatively decomposed. Cauchy functions and Hadamard matrices were introduced for hash center generation optimization, aiming to achieve more efficient hash retrieval and search capabilities. The subject of the research is to optimize the intelligent detection and search efficiency of communication image signals using improved DRH search techniques and to solve the efficiency and accuracy problems of existing methods in large-scale data processing. The research is motivated by the rapidly growing demand for image signal processing in modern communication systems, especially in the task of intelligent detection and search of large-scale, multi-labelled communication image signals, where traditional methods are difficult to meet the requirements of real-time and accuracy. The contribution of the research is to propose an improved DRH that combines the Cauchy function and Hadamard matrix, which effectively enhances the detection and retrieval efficiency of communication image signals. The method is capable of generating more compact and discriminative hash codes, which are suitable for large-scale image data processing. This research is divided into six sections, Section II systematically analyzes and summarizes the existing related work. Section III proposes a communication image signal detection and search model based on a deep hash retrieval technique constructed by the research. Section IV demonstrates the performance of the improved model through experimental tests. Discussion is given in Section V. Section VI summarizes the research results and proposes directions for future research.

## II. Related Work

With the developing communication technology, the transmission and processing of communication signals become increasingly important in various fields. CIS covers a wide range from traditional image communication to modern multimedia communication, characterized by large data volume and high diversity. Therefore, intelligent detection and search of CIS becomes a highly focused research direction. To improve the image communication performance of existing optical cameras, Nguyen D T et al. proposed a novel method for extracting image signal features of interest by combining low-density parity check codes. This method had more advantages in teaching traditional image communication processing techniques [5]. To improve the signal detection accuracy of the fifth generation wireless communication system, You Y H et al. proposed a new detection method by combining complex secondary synchronization signals. This method was highly effective and greatly reduced complexity compared to similar methods [6]. Li K et al. found that traditional image signal quality detection methods were no longer able to meet the requirements of existing medical information detection. Therefore, this team introduced the concepts of fully known signals and statically known signals using deep neural networks for optimization, and finally proposed a new detection method. This new method ensured the preservation of task-related information while denoising, which had strong usability [7]. Wen X et al. believed that autoencoders using convolutional neural networks still had insufficient capabilities in extracting spatiotemporal information from the network. Given this, the team proposed an image signal detection model using a pseudo 3D encoder and multi-level storage mechanism. The detection performance of this model was superior to other similar methods on three datasets [8]. Orsuti D et al. In order to improve the retrieval of communication image signals, the researchers finally proposed a communication image signal recovery method by combining full convolutional neural networks for non-iterative and robust phase recovery. The experimental results show that the performance of this method is compared with that of a conventional KK receiver using 4x digital upsampling, which can achieve 7% hard verdict forward error correction and 1.8 dB increase in receiver sensitivity [9].Kumar S et al. found that content-based image signal retrieval is susceptible to degradation of retrieval accuracy with the adoption of cloud storage. For this reason, the researchers proposed a new retrieval model after incorporating a nonlinear stacking algorithm. Experimental results show that the accuracy of this new model is significantly improved and more robust compared to the existing methods [10].

Hash retrieval technology is a technique used for quickly searching and retrieving large-scale datasets. It converts data into a set of fixed length hash values and uses these hash values to organize and index the data. Qin et al. found that most existing hash techniques only focused on the semantic similarity between image pairs, ignoring the ranking information of retrieval results. Therefore, this team proposed a new type of DRH by combining the deep top similarity theory. This method was more effective than traditional methods on several multi-label datasets [11]. To expand the application of hashing technology in image representation and approximate queries, Shuai C et al. proposed a principal component analysis hashing technique by combining longer binary codes and mapping vector rotations. This method achieved more types of partitions and significantly improved performance [12]. To further improve the speed and accuracy of hash technology for cross-modal information retrieval, Shen X et al. proposed a clustering driven deep adversarial hash model by combining end-to-end thinking. This model accurately maximized the distance calculation between images and texts with different labels, which had better performance [13]. Zhang D et al. believed that when the hash length changed, the hash model needed to be retrained. This consumed additional computing power and reduced its application scalability. Therefore, this team proposed a multi-hash model for cross-media retrieval. This model did not require training when the hash length changed, which was superior to some competitive shallow and deep hash methods [14]. Zhu L et al. In order to solve the problem of high storage cost and slow retrieval efficiency during multimedia retrieval, the researchers proposed a retrieval enhancement method after combining hash retrieval techniques. The experimental results show that under the reinforcing effect of the method makes the retrieval of Hamming distance calculation significantly accelerated, and the cost of retrieval time is effectively reduced [15].Sabahi F et al. found that the existing image retrieval reordering technique has the problem of high computational complexity, for this reason, the researchers proposed a novel and computationally efficient image retrieval reordering method after combining with hash retrieval technology. Experimental results show that this new method generally outperforms other traditional methods in terms of computational efficiency and retrieval performance [16].

In summary, many researchers have explored the detection of communication image information and proposed some remarkable research results. Meanwhile, the continuous development and evolution of hash retrieval technology makes its application wider. Therefore, the study attempts to combine these two and innovatively optimize hash technology to improve its performance in various modules and promote the development of CIS detection.

## III. Construction of an Intelligent Detection and Search Model for Communication Signals based on Deep-Re-Hash Retrieval Technology

This study first analyzes traditional DRH and constructs an image signal detection model under this algorithm. Secondly, the shortcomings of DRH are elaborated, and the Cauchy concept function and Hamada matrix are introduced for hash center generation optimization. Finally, a new detection and search model is proposed.

### A. *Communication Image Signal Processing Model Based on Deep-Re-Hash*

DRH can map high-dimensional data to low-dimensional binary encoding [17]. By learning the deep features of data, DRH can convert the original image signal into binary encoding, thereby achieving efficient processing and transmission of image signals. To generate binary hash codes, DRH typically adds n+1 fully connected layers for optimization [18]. This layer guides the generation of the required number of neurons and the length of the hash code. Fig. 1 shows the structure of DRH.

In Fig. 1, after inputting the initial image signal data, DRH uses a deep neural network to extract image features, and then converts these features into binary hash codes in Hamming space through a hash function. This process typically involves converting data, such as images, text, etc., into a compact binary representation, with key steps including data representation, feature extraction functions, binarization process, and hash code generation. The feature extraction function is represented by Eq. (1).

$$Z = f(X, \theta) \tag{1}$$

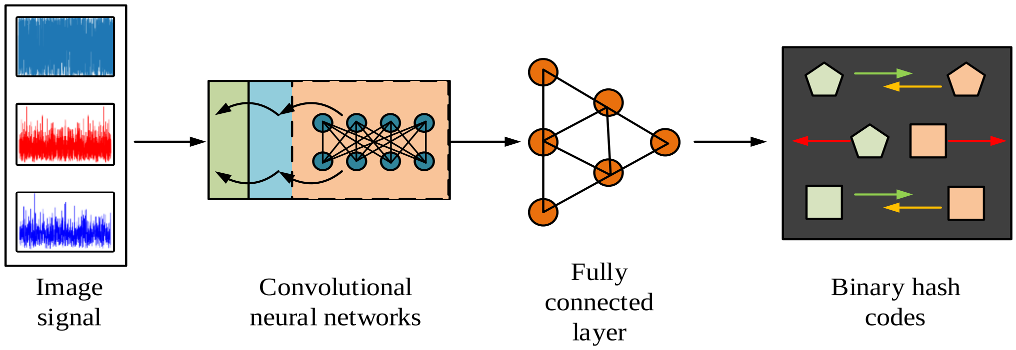



Fig. 1. Structure diagram of DRH.

In Eq. (1), $Z$ represents the feature set of the input data, which is a real number vector. $\theta$ is a model parameter. $X$ refers to the initial image input. $f(X,\theta)$ represents a deep neural network function. The binarization process is represented by Eq. (2).

$$H(X) = sign(Z), sign(z_i) = \begin{cases} 1, if z_i \geq 0 \\ 0, otherwise \end{cases} \tag{2}$$

In Eq. (2), $z_i$ represents the $i$ th element in the feature set. If $z_i$ is greater than or equal to 0, the corresponding hash code point is set to 1. Otherwise, it is set to 0. $sign$ represents a binarization function. The final hash code is a vector composed of 0 and 1, representing the hash code of the input data $X$. The hash function, as a key point that can directly affect the stability of the conversion result, should be consistent in the same class of image signals, but inconsistent in different classes of image signals. The hash function is represented by Eq. (3).

$$Hash(X) = sign(f(X,\theta)) \tag{3}$$

In Eq. (3), $sign$ maps each element in the feature vector to {− 1,1}, thereby generating a hash code. In similar images, DRH usually has two retrieval strategies, namely Hamming sorting and Hamming retrieval. Fig. 2 is a schematic diagram of two retrieval strategies.

In Fig. 2, both Hamming sorting and Hamming retrieval involve using Hamming distance to process data. Hamming sorting sorts data items based on their Hamming distance from the query item, while Hamming retrieval searches for data items that have a specified Hamming distance from the query item [19]. The Hamming distance is used to measure the difference between two equally long strings, that is, the number of different characters at the same position. In the context of hash retrieval, the Hamming distance is represented by Eq. (4).

$$D_H(HM(X), HM(Y)) = \sum_{i=1}^{L} [HM(X)_i \neq HM(Y)_i] \tag{4}$$

In Eq. (4), $L$ represents the length of the hash code. $HM(X)$ refers to inputting the hash code of $X$. $HM(Y)$ refers to inputting the hash code of $HM(Y)$. $HM(X)_i \neq HM(Y)_i$ represents an indicator function, which takes a value of 1 when these two are not equal, and 0 otherwise. On this basis, Hamming sorting is to calculate the Hamming distance between a given query hash code $HM(Q)$ and each hash code $HM(X)$ in the database, and then sort it according to this distance. The Hamming search is represented by Eq. (5).

$$Search(HM(Q),\tau) = \{X \,|\, D_H(HM(Q), HM(X) \leq \tau)\} \tag{5}$$

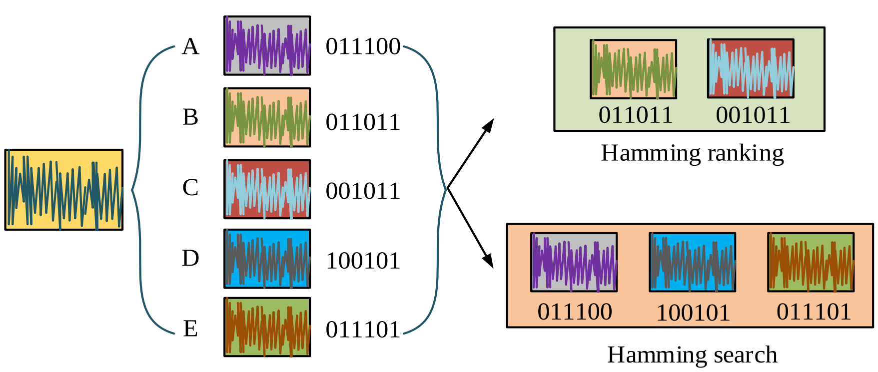



Fig. 2. Schematic diagram of hamming sorting and hamming retrieval.

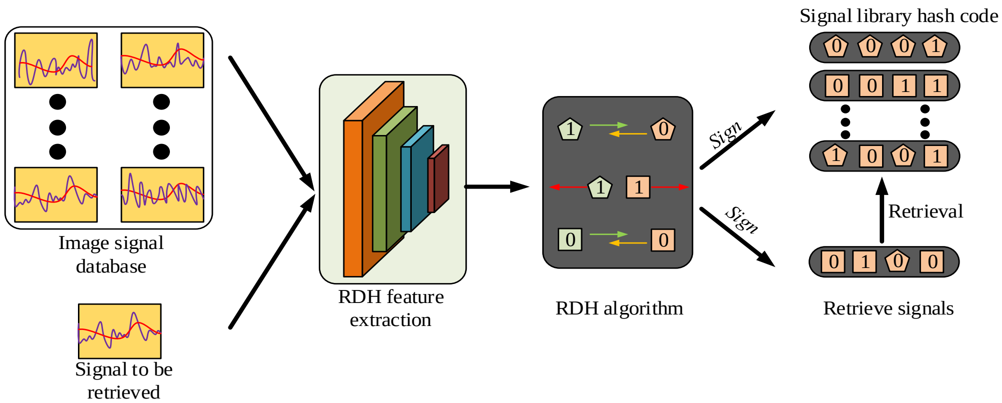



Fig. 3. DRH image signal detection model structure.

In Eq. (5), $\tau$ represents a predetermined threshold. All hash codes $HM(X)$ in the database were retrieved so that their Hamming distance from the query hash code $HM(Q)$ does not exceed $\tau$. In practical applications, Hamming sorting and Hamming retrieval are commonly used for fast approximate retrieval, especially in large-scale image or document databases. In summary, this study proposes a CIS detection model in combination with DRH. Fig. 3 shows the model structure.

In Fig. 3, first, the signal database and the information to be queried are inputted. Then, these are extracted by the feature extraction module of DRH. After completion, these features are fed into a deep neural network to learn more complex feature representations. The network output is binarized using an adjusted $sign$ to generate a binary hash code. Finally, these hash codes are used for fast image retrieval, allowing the system to effectively match and search for image data.

*B. Construction of a Communication Image Detection Model based on Improved Deep-Re-Hash*

DRH provides an effective way to process and retrieve large amounts of image data in image signal detection. The hash center is a point in the hash space that represents the center position of a certain class or cluster of data [20]. The hash center is represented by Eq. (6).

$$C_j = \arg\min_{C_j} \sum_{i=1}^{N} y_{ij} \cdot D(H(x_i), C_j) \tag{6}$$

In Eq. (6), $C_j$ refers to the hash center of category $j$. $x_i$ represents the $i$ th data point in the training dataset. $H(x_i)$ is a hash representation of data point $x_i$, typically generated by deep networks. $y_{ij}$ represents an indicator variable. If the data point $x_i$ belongs to category $j$, then $y_{ij}$ is equal to 1, otherwise it is 0. $D$ represents distance measurement. $N$ refers to the total data points in the training dataset. Fig. 4 shows the hash centers at two different dimensions.

Fig. 4(a) and Fig. 4(b) are schematic diagrams of hash centers at both three-dimensional and four-dimensional scales. The distance between the individual hash code and the hash center is 1. In space, there also exists a consistency relationship with the three-dimensional hash center and hash code. In addition, considering the complex environment of image signals, this study conducts hash center generation calculations for single label and multi-label image signal data, respectively. Fig. 5 shows the generation of hash centers in both environments at this time.

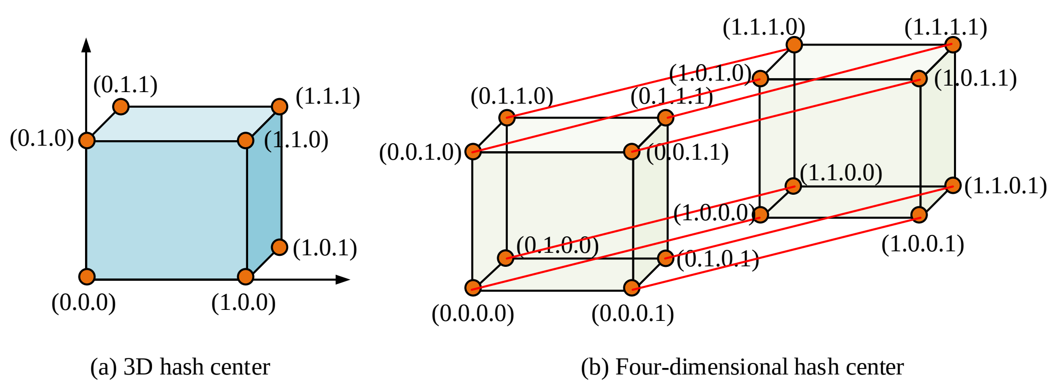
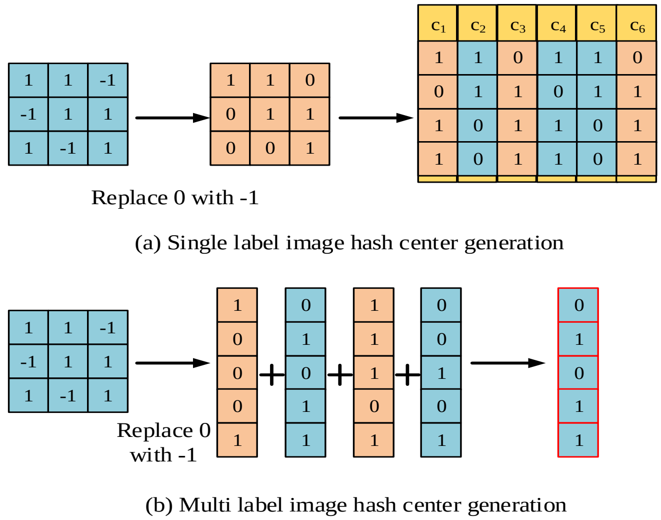



Fig. 4. Schematic diagram of multi-dimensional hash center position.




(a) Single label image hash center generation

(b) Multi label image hash center generation

Fig. 5. Hash center generation for single-label and multi-label image data.

Fig. 5(a) shows the generation of hash centers for single label and multi label image data in various scenarios. In single label image data, each image belongs to only one category. Hash centers are typically representative hash codes of categories. The hash center can be directly obtained by calculating the average value of all image hash codes within the same category. In multi-label image data, each image can belong to multiple categories simultaneously. In this case, the generation of hash centers becomes even more complex, as the impact of multiple labels on each image needs to be considered. The hash center of single label image data is represented by Eq. (7).

$$C_j^s = \frac{1}{N_j}\sum_{i=1}^{N} y_{ij}\cdot H(x_i) \tag{7}$$

The hash center of multi-label image signal data is represented by Eq. (8).

$$C_j^m = \frac{1}{\sum_{i=1}^{N} y_{ij}}\sum_{i=1}^{N} y_{ij}\cdot H(x_i) \tag{8}$$

In the case of multiple labels, $y_{ij}$ can be a binary indicator variable or a real value representing the confidence or weight belonging to that category. The calculation of hash centers requires accumulating the contribution of each category on all images, taking into account that each image may contribute to multiple categories. At this point, whether it is single label or multi-label image data, the hash center should have independence and balance, represented by Eq. (0).

$$\begin{cases} B^T B = I \\ B^T 1 = 0 \end{cases} \tag{9}$$

In Eq. (9), $I$ refers to an identity matrix. In model training, the learning efficiency of hash codes is highest when the hash code is infinitely close to the hash center. To further guide the implementation of this process, this study introduces Cauchy functions to improve the generation process of hash codes. This enables the generated hash code to better reflect the similarity between images while preserving image features. By using the cumulative distribution function of Cauchy distribution, points in deep feature space can be mapped to points in hash space [21], represented by Eq. (10).

$$Y_{cj}(Z`) = \frac{1}{\pi}\arctan\left(\frac{Z`-C_i}{\gamma}\right)+\frac{1}{2} \tag{10}$$

In Eq. (10), $H_{cj}(Z`)$ refers to the mapping value of the feature vector $Z`$ relative to the hash center $C_i$ of class $i$. $\gamma$ represents a scale parameter of the Cauchy distribution. After completing the generation of continuous hash codes with probability characteristics, the processing of hash codes continued to be explored in the experiment. Hadamard matrix can be used as a special hash function to generate hash codes. Hadamard matrix is a specific orthogonal matrix whose elements only contain 1 and -1, and its orthogonality ensures the dispersion of hash codes, represented by Eq. (11).

$$H = Had\cdot Z \tag{11}$$

In Eq. (11), $Had$ represents the Hadamard matrix. The Hadamard matrix serves as the hash center training and sampling matrix, which satisfies Eq. (12).

$$\begin{cases} Had^T\cdot Had = KI_K \\ Had\cdot Had^T = KI_K \end{cases} \tag{12}$$

In Eq. (12), $I_K$ refers to a $K$ order identity matrix. In the $K$ dimensional Hamming space, if the feature vectors of a set of images are orthogonal to each other, the Hamming distance between the two also meets the requirements described in Eq. (9). Finally, the result generated by the user hash center after combining the Cauchy probability function with Hadamard is represented by Eq. (13).

$$B = sign(\frac{1}{\pi} arc\tan(\frac{Had \cdot Z - C}{\gamma})) \tag{13}$$

In Eq. (13), $B$ refers to the final generated binary hash code. $C$ is a Cauchy center. In summary, after combining Cauchy function and Hadamard matrix to optimize the generation of hash center points, an improved DRH image signal detection search model using deep learning framework is proposed in Fig. 6.

In Fig. 6, firstly, CIS undergoes standardized preprocessing to adapt to the input requirements of the deep learning network. Then, the preprocessed image is feature extracted through a deep neural network. Next, the extracted continuous feature vectors are mapped to a new feature space by the Cauchy probability function, increasing resolution and enhancing the dispersion of the hash code through Hadamard matrix transformation. By utilizing these transformed features, this model calculates the hash center points for each category through optimization algorithms, which guide the generation of compact and discriminative hash codes during the binarization. During model training, similarity learning is also included to ensure that hash codes can reflect the similarity between images. Finally, during the retrieval phase, for a given query image signal, this model will quickly retrieve the image signal in the database with the smallest Hamming distance from its hash code. This model may undergo subsequent sorting and filtering to display the most relevant search results.

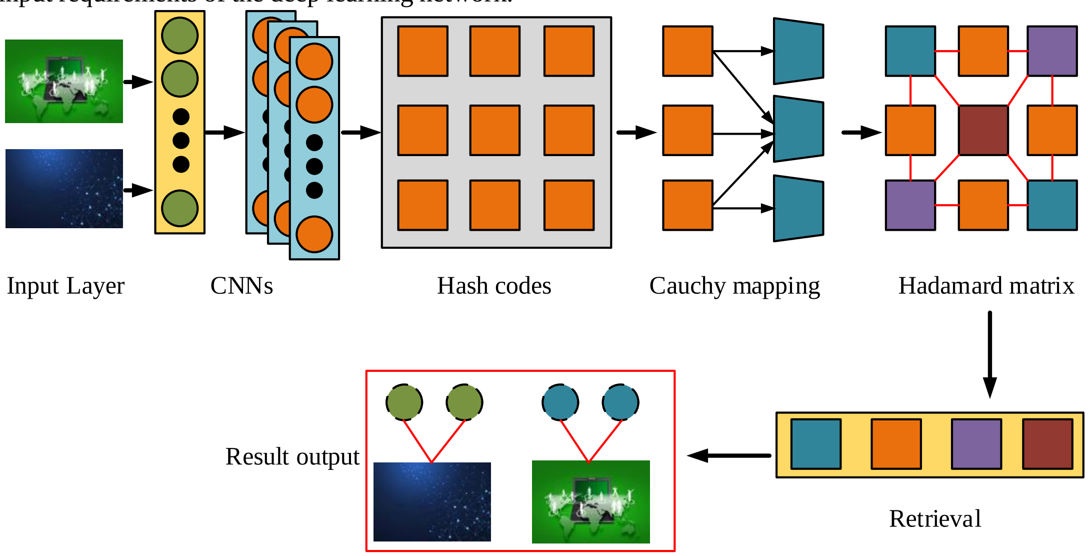



Fig. 6. A communication image signal detection model under improved DRH.

## IV. Experimental Testing

A suitable experimental environment was established. Firstly, performance testing was conducted on the algorithm module in the improved DRH, and the training results of the algorithm were compared with algorithms of the same type. Secondly, simulation tests were conducted on the improved DRH detection model to verify its superiority in image signal detection. Tests show that the improved DRH algorithm is particularly suitable for datasets with multidimensional features, such as communication image signal data. Its advantage lies in the processing of large-scale, high-diversity data types, especially in the case of high data dimensionality, the improved DRH algorithm can effectively reduce the computational complexity and improve the retrieval efficiency through the optimized generation of hash codes. Therefore, the algorithm is more suitable for image signal datasets containing a large number of image features with multiple labels, such as CSCOCO and Caltech 256.Especially when dealing with this type of multi-label, high-dimensional data, the algorithm is able to significantly improve the checking rate and retrieval accuracy through the hash center optimized by the Hadamard matrix and the Cauchy function, and the MAP value is significantly higher than that of other algorithms.

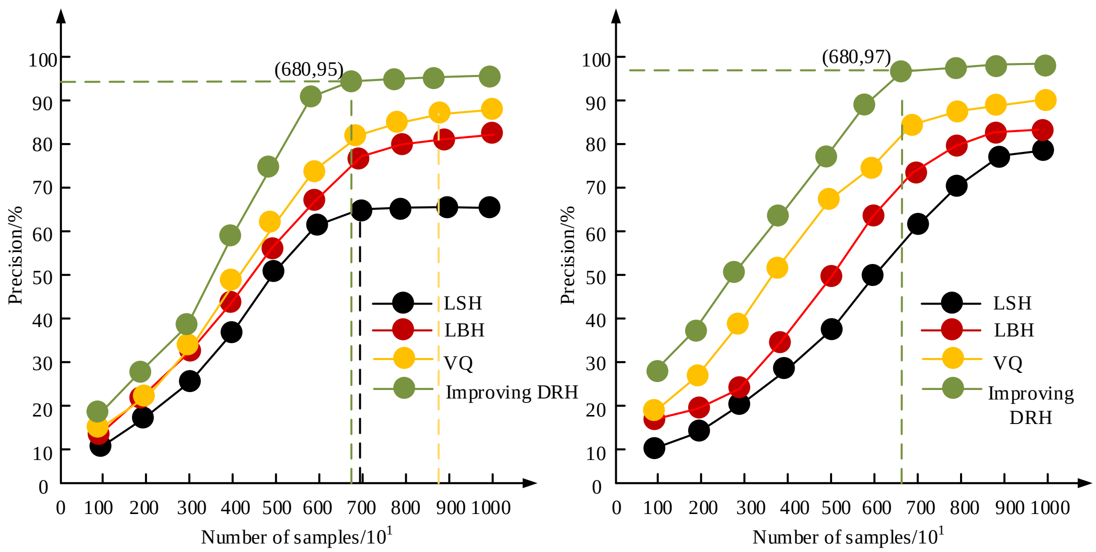
### A. Model Performance Testing

A suitable experimental environment was established to verify the effectiveness of the proposed improved DRH image signal detection. Two widely used CIS datasets were introduced, namely CSCOCO and Caltech 256. CSCOCO is a dataset used for image keypoint detection tasks, containing over 200000 images and corresponding annotations. Caltech 256 is a larger dataset that includes 100000 images of different categories. Table I shows the specific experimental testing environment configuration.

Based on the above parameter configuration, the dataset was divided into training and testing sets in an 8:2 ratio. To better fit the characteristics of the test object, the study used precision as the testing indicator. Meanwhile, similar communication image information detection algorithms were introduced, such as Locality-Sensitive Hashing (LSH), Learning-Based Hashing (LBH), and Vector Quantization (VQ). Fig. 7 shows the test results.

TABLE I. ENVIRONMENTAL CONFIGURATION AND PARAMETERS

| Environment | Name | Configuration |
|---|---|---|
| Hardware | CPU | Intel Core i7 |
| | Graphics card | NVIDIA GeForce GTX 1060 |
| | Memory | 8GB RAM |
| | Hard disk | 15T |
| Software | Operating environment | Windows 10 |
| | Python | Python 3.8 |
| | Deep learning framework | TensorFlow |
| | Data set | CSCOCO、Caltech 256 |
| | Development tool | Visual Studio Code |




(a) Training set (b) Test set

Fig. 7. Performance effects of different algorithms.

Fig. 7(a) shows the performance test results of four algorithms on the training set. Fig. 7(b) shows the performance test results of four algorithms on the test set. In both datasets, the precision of these four algorithms tends to stabilize with increasing sample size. Overall, this improved DRH had the best performance, with a highest precision of 95% in the training set and a minimum sample size of 6800. In the test set, the highest precision of the improved DRH was 97%, with a sample size of 680. Therefore, the improved DRH showed better algorithm performance in both training and testing results. The study continued to use Mean Average Precision (MAP) as an indicator and the length of hash codes and Hamming distance distribution as test variables to discuss the changes in the four algorithms in Fig. 8.

Fig. 8(a) shows the hash length detection results of four algorithms in CSCOCO. Fig. 8(b) shows the hash length detection results of the four algorithms in Caltech 256. Fig. 8(c) shows the Hamming length distribution detection results of four algorithms in CSCOCO. Fig. 8(d) shows the Hamming length distribution detection results of the four algorithms in Caltech 256. As the hash length continued to increase, the MAP of these four algorithms continued to increase. But when the hash length approached an extreme value, the MAP was at its maximum. In the above data, the improved DRH generally had a higher MAP as the hash length changed, with a maximum value of 94%. The hash length at this point was 64 bits. In addition, under different Hamming distance distributions, the improved DRH's MAP was significantly better than other methods, with the optimal MAP of 90% and a Hamming distance distribution value of 2. In theory, longer hash codes can provide more refined feature representations, which may result in higher accuracy during retrieval. However, excessively long hash codes can also lead to dimensional disasters, resulting in reduced retrieval efficiency. In addition, if a retrieval system can effectively map the similarity of images to the Hamming distance of hash codes, then retrieval within a smaller Hamming distance range should achieve higher accuracy and MAP.

## B. *Model Performance Simulation Testing*

The study randomly selected four images each from CSCOCO and Caltech 256 for simulation testing to verify the improved DRH's CIS detection performance. Fig. 9 shows the combined image.

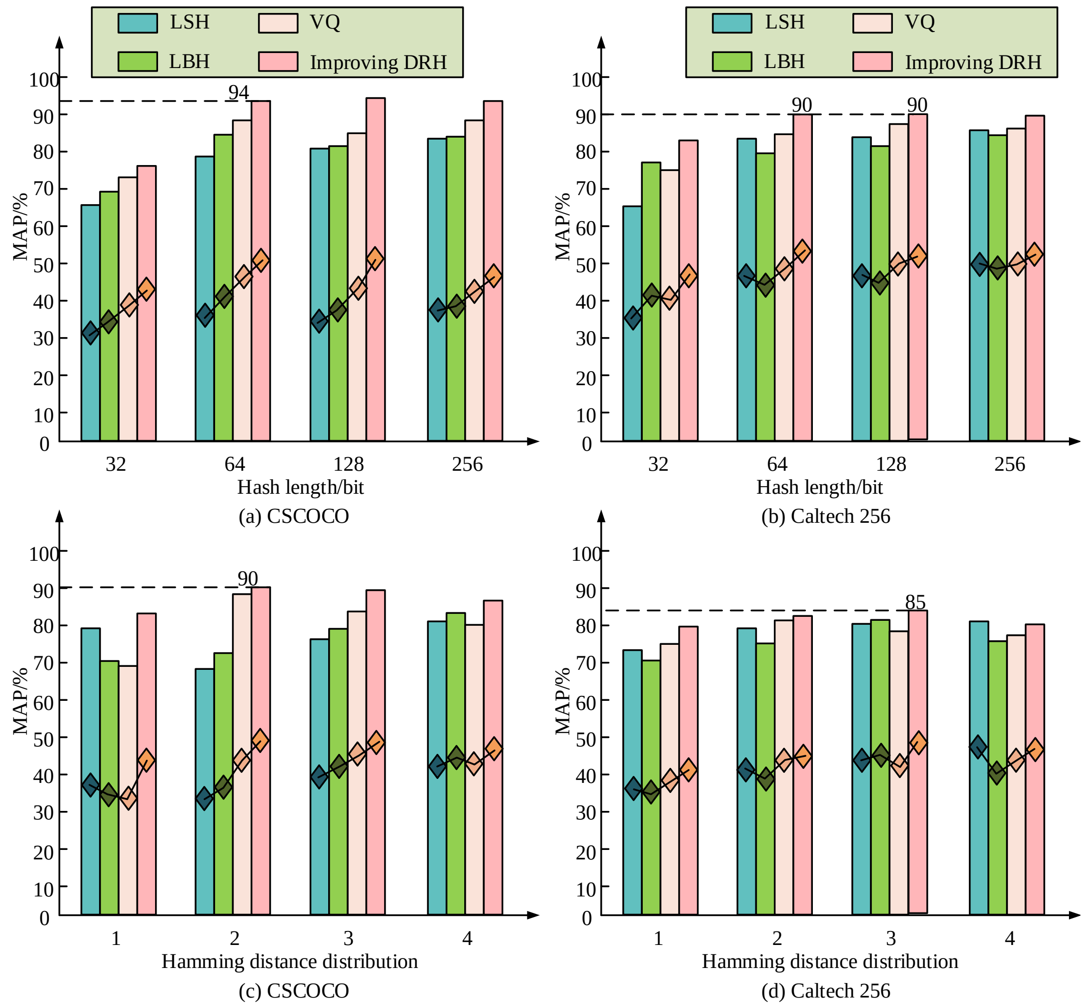



Fig. 8. Test results of indicators for different models under two types of data.

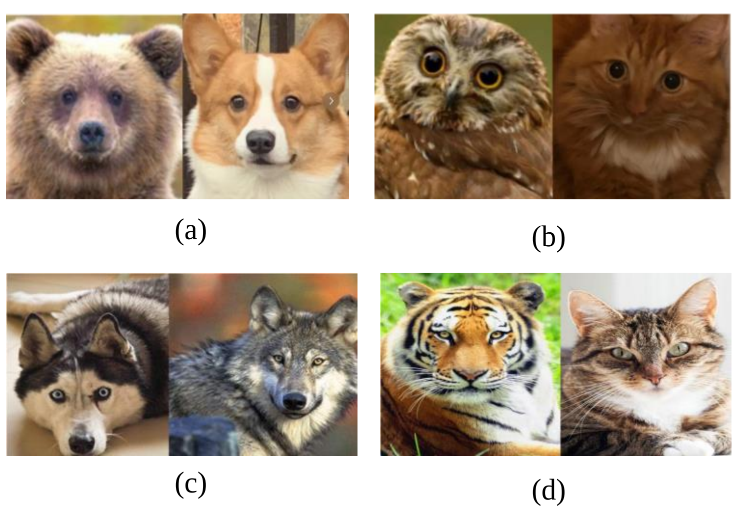



Fig. 9. Four communication image signals to be detected.

Combining these four image signals to be detected in Fig. 9, this study introduced CIS detection models of the same type, such as Content-Based Image Retrieval (CBIR), Feature Matching Search (FMS), and traditional DRH. The previously mentioned previous studies such as the method proposed by Orsuti D et al, the method proposed by Kumar S et al., the method proposed by Zhu L et al. and the method proposed by Sabahi F et al. were also selected for comparison and tested in terms of image signal retrieval similarity and detection time and the results of the test are shown in Table II.

TABLE II. THE DETECTION RESULTS OF FOUR MODELS ON DIFFERENT IMAGES

| Image | Molde | Image signal retrieval similarity/% | Retrieval time/s |
|---|---|---|---|
| Figure a | CBIR | 93.7 | 15.4 |
| | FMS | 80.7 | 13.1 |
| | DRH | 89.4 | 10.5 |
| | The method proposed by Orsuti D et al. | 88.6 | 9.7 |
| | The method proposed by Kumar S et al. | 85.3 | 8.3 |
| | The method proposed by Zhu L et al. | 85.7 | 8.6 |
| | The method proposed by Sabahi F et al. | 86.9 | 8.9 |
| | Improving DRH | 83.3 | 7.1 |
| Figure b | CBIR | 92.1 | 16.5 |
| | FMS | 83.4 | 13.4 |
| | DRH | 87.4 | 8.7 |
| | The method proposed by Orsuti D et al. | 88.2 | 9.3 |
| | The method proposed by Kumar S et al. | 86.3 | 8.9 |
| | The method proposed by Zhu L et al. | 83.1 | 7.7 |
| | The method proposed by Sabahi F et al. | 83.5 | 7.2 |
| | Improving DRH | 81.1 | 5.3 |
| Figure c | CBIR | 84.9 | 19.5 |
| | FMS | 81.3 | 19.7 |
| | DRH | 85.8 | 14.6 |
| | The method proposed by Orsuti D et al. | 85.4 | 13.7 |
| | The method proposed by Kumar S et al. | 86.6 | 12.2 |
| | The method proposed by Zhu L et al. | 83.9 | 13.1 |
| | The method proposed by Sabahi F et al. | 83.5 | 12.8 |
| | Improving DRH | 81.7 | 10.7 |
| Figure d | CBIR | 79.4 | 24.7 |
| | FMS | 72.4 | 16.7 |
| | DRH | 72.4 | 14.2 |
| | The method proposed by Orsuti D et al. | 70.2 | 8.9 |
| | The method proposed by Kumar S et al. | 69.8 | 10.2 |
| | The method proposed by Zhu L et al. | 65.7 | 9.7 |
| | The method proposed by Sabahi F et al. | 67.4 | 8.8 |
| | Improving DRH | 64.8 | 7.6 |

Combining the four groups of extremely similar different species of animals in Fig. 9, if the detection similarity is higher, it indicates that the model's ability to distinguish CIS is insufficient. On the contrary, it indicates that the model can distinguish animal images from each group and meet the requirements of image signal differentiation. Compared with other models such as CBIR, FMS, and conventional DRH, the improved DRH model showed the shortest detection time, especially in Fig. 9(a) and Fig. 9(d), which were shortened by about 8.3 and 17.1 seconds, respectively, and demonstrated a high detection efficiency. In addition, compared with several previous studies, such as the models proposed by Orsuti D et al., Kumar S et al., Zhu L et al., Sabahi F et al., the detection of the improved DRH model is still faster, with the time consumed ranging from 7.1 to 10.7 seconds, respectively, which is lower than that of all the compared models. In terms of image signal retrieval similarity, although the similarity of the improved DRH model is slightly lower than that of the CBIR and FMS models, it still performs stably with a range of retrieval similarity between 64.8% and 83.3%, which shows the better differentiation ability of this model, especially in complex environments where it can maintain a low false detection rate. In the image of Figure d, the similarity of the improved DRH model is 64.8%, which is about 14.6% less compared to the CBIR model, but its detection time is shortened by 17.1 seconds, indicating that the improved DRH model is more suitable for application in time-sensitive scenes. The hash code has a length of 64 bits and a Hamming distance distribution of 2. Fig. 10 shows the visualization result at this time.

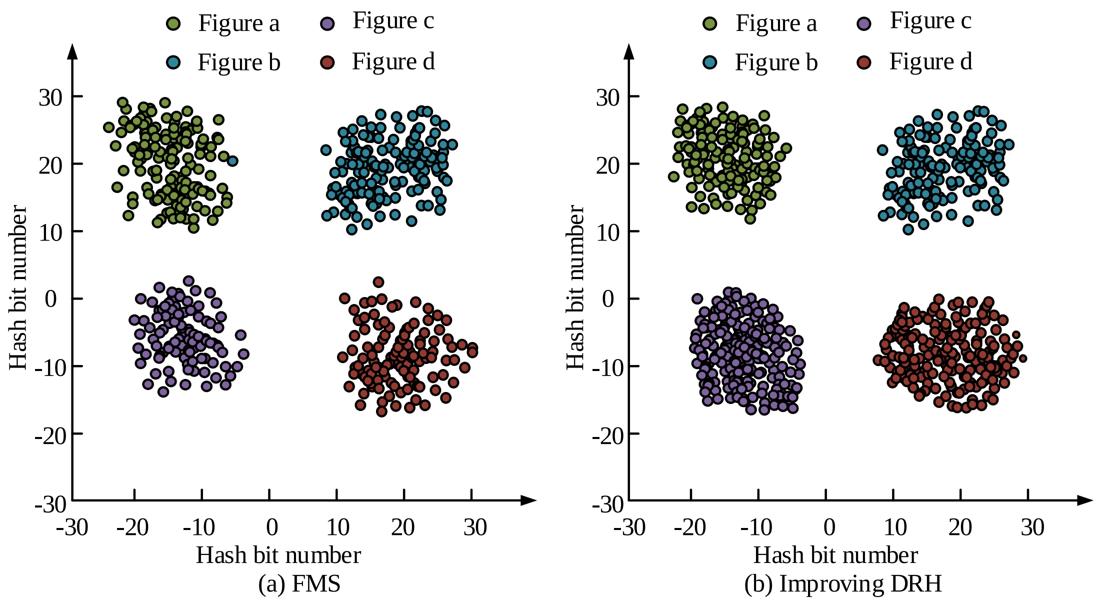



Fig. 10. Image visualization results of two algorithms.

Fig. 10 (a) shows the visualization results of four images under FMS. Fig. 10 (b) shows the visualization results of four images under improved DRH. The hash code of FMS was relatively scattered and chaotic, with poor discrimination. On the other hand, the improved DRH generated hash codes that were highly aggregated and had very clear edges. The reason for this is that the improved DRH utilizes Cauchy functions for scaling, while also using Hadamard matrices to generate hash centers and guide hash learning. Finally, the study used a comprehensive scoring method to evaluate storage occupancy rate, detection satisfaction, and time consumption as indicators. Indicator tests were conducted on 10 images under two models, with evaluation values ranging from (-60,60) in Fig. 11.

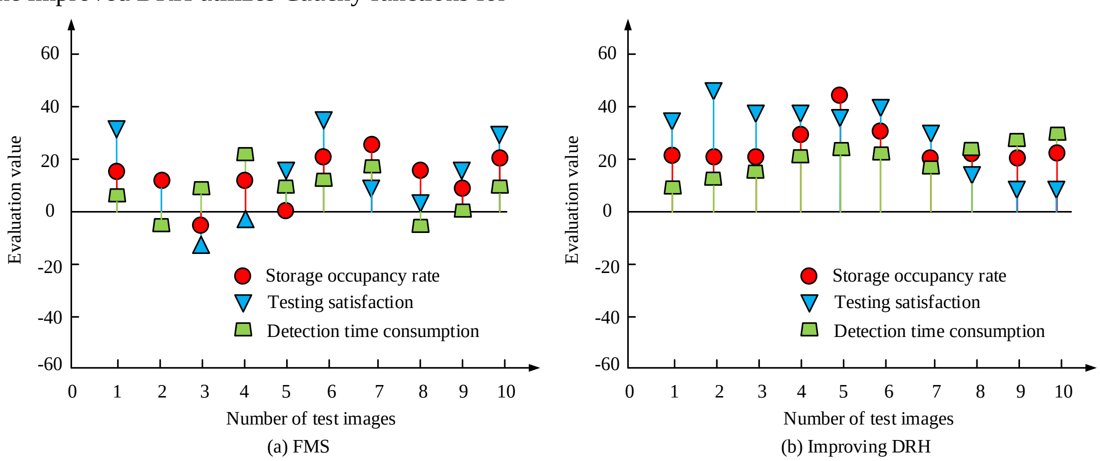



Fig. 11. Multi indicator scoring results of two types of algorithms.

Fig. 11(a) shows the three indicator scores of FMS. Fig. 11(b) shows the three indicator scores of the improved DRH. In FMS, when the detected image signals were 2, 3, 4, 8, and 9, the model storage occupancy, detection satisfaction, and detection time ratings were low, showing unstable fluctuations. On the other hand, the improved DRH had a positive rating for all three indicators. At this point, the storage occupancy rate score was close to 45 points, the detection satisfaction score was close to 50 points, and the detection time score was close to 30 points. In summary, the proposed improved image signal model has certain advantages and stability.

## V. Discussion

The study proposes an improved deep hashing algorithm that combines the Cauchy function and Hadamard matrix, and the method optimizes the retrieval performance of image signals by generating more compact and discriminative hash codes. The experimental results show that the checking accuracy of the proposed method under study reaches 97% and 95% on CSCOCO and Caltech 256 datasets, respectively. In addition, the MAP value of the model reaches up to 90% when the hash code length is 64bit, which indicates that the research has significantly improved the accuracy while ensuring the retrieval speed. By optimizing the distribution of Hamming distances, the model is able to achieve high-precision similarity search within a small range of Hamming distances. In comparison with other related studies, the improved DRH algorithm shows unique advantages. Orsuti D et al. showed that the feature extraction of image signals using CNN, although it can obtain better results on small-scale datasets, the computational overhead of the model increases significantly in large-scale, multi-labeled datasets, resulting in a decrease in the retrieval speed. In contrast, the study reduces the computational complexity in the convolutional network and improves the processing speed through the optimal generation of hash codes. In addition, it is found that the improved DRH algorithm achieves the highest MAP value of 90% when the Hamming distance is 2, while the MAP value of the other methods is only about 70% under the same conditions. This result shows that the proposed method of the study is still able to maintain a high similarity retrieval accuracy in the low-dimensional hash space of large-scale datasets. This is in contrast to the results of Wu G et al. whose proposed algorithm rapidly decreases the retrieval accuracy when the Hamming distance is small [22]. It can be shown that the study effectively solves such problems through the improved hash center generation mechanism, which enables better performance to be maintained when performing low-dimensional retrieval in large-scale communication image signals.

In summary, the improved DRH algorithm proposed by the study successfully improves the retrieval efficiency and accuracy of large-scale communication image signals through the optimization of the Cauchy function and Hadamard matrix. By comparing with other studies, it can be seen that the algorithm performs superiorly in dealing with multi-label and high-dimensional data, especially in the optimization of retrieval accuracy and Hamming distance with unique advantages. Future work can continue to explore the application of the model in different types of data and further optimize its computational performance to cope with the processing demands of larger-scale signal datasets.

## VI. Conclusion

With the developing communication technology, the transmission and processing of CIS becomes more important in various fields. In this context, intelligent detection and search of CIS becomes a highly focused research direction. In view of this, firstly, this study constructed an image signal detection search model for traditional DRH. Secondly, the Cauchy concept function and Hadamard matrix were introduced to optimize the generation of hash centers. Finally, an improved DRH image signal detection model was proposed. When the test samples were 680, the highest precision of the new model was 97%. Compared with the same type of algorithm, when the Hamming distance is 2, at this time, the MAP value of the improved DRH algorithm is up to 90%, and the hash length is 64bit, which is significantly better than other algorithms. Simulation tests show that the detection similarity of the improved DRH model can be as low as 64.8%, and the fastest detection speed is 7.6 s. At this time, the similarity is reduced by about 14.6% compared with the CBIR model, and the time is shortened by 17.1 seconds. In addition, in the visualization results, the hash code generated by the improved DRH model is extremely aggregated with very clear edges, which is clearly superior. The highest storage occupancy score, detection satisfaction score, and detection time consumed score for this new model are 45, 50, and 30, respectively, which are higher than all other three types of models. In summary, the proposed improved DRH should not only have efficient detection and search capabilities, but also consider the diversity and dynamism of CIS in practical applications. In the future, this model can be further optimized to consider more practical application scenarios to promote the CIS processing.

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