

Asymmetric Hash Code Learning for Remote Sensing Image Retrieval

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Abstract—Remote sensing image retrieval (RSIR), aiming at searching for a set of similar items to a given query image, is a very important task in remote sensing applications. Deep hashing learning as the current mainstream method has achieved satisfactory retrieval performance. On one hand, various deep neural networks are used to extract semantic features of remote sensing images. On the other hand, the hashing techniques are subsequently adopted to map the high-dimensional deep features to the low-dimensional binary codes. This kind of methods attempts to learn one hash function for both the query and database samples in a symmetric way. However, with the number of database samples increasing, it is typically time-consuming to generate the hash codes of large-scale database images. In this paper, we propose a novel deep hashing method, named asymmetric hash code learning (AHCL), for RSIR. The proposed AHCL generates the hash codes of query and database images in an asymmetric way. In more detail, the hash codes of query images are obtained by binarizing the output of the network, while the hash codes of database images are directly learned by solving the designed objective function. In addition, we combine the semantic information of each image and the similarity information of pairs of images as supervised information to train a deep hashing network, which improves the representation ability of deep features and hash codes. The experimental results on three public datasets demonstrate that the proposed method outperforms symmetric methods in terms of retrieval accuracy and efficiency. The source code is available at https://github.com/weiweisong415/Demo_AHCL_for_TGRS2022.

Index Terms—Remote sensing image, scene retrieval, deep neural network, hashing learning, asymmetric.

I. INTRODUCTION

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AS a result of the rapid development of Earth observation technologies, remote sensing images collected by satellites or aerial vehicles have been dramatically enhanced both in volume and resolution. How to effectively manage and analyze these massive amounts of remote sensing images has become an urgent challenge. Remote sensing image retrieval (RSIR), which aims at searching for a set of similar images or scenes to a given query image, has been attracted wide attention in the remote sensing community [1].

In early research of RSIR, most methods exploited annotated tags (e.g., geographical location, acquisition time, or sensor type) to search similar images. Since the used annotated tags can not fully represent image content, this kind of methods usually delivers imprecise retrieval results. By contrast, content-based image retrieval (CBIR) methods employ image features to represent the visual content of remote sensing images, which obtains satisfactory performance. Generally speaking, a CBIR framework includes two main modules: feature extraction and a similarity measure. Fig. 1 demonstrates a typical retrieval framework for RSIR.

For the feature extraction procedure, the query images and database images are all represented by the designed feature descriptors. The extracted features can be divided into hand-crafted features and deep features. The hand-crafted features include low-level features and mid-level features. In the past decades, low-level features were widely used in RSIR, such as texture features [2], spectral features [3], and shape features [4], [5]. In addition, various encoding techniques, e.g., bag-of-visual words (BoVW) [6], Fisher vector (FV) [7], and vector of locally aggregated descriptors (VLAD) [8] were also exploited to encode the low-level features into mid-level features, which delivered satisfactory retrieval results. However, the representation ability of hand-crafted features is limited to accurately describing the semantic information of remote sensing images, which is also called as “semantic gap”. With the progress of deep learning in the computer visual field, convolutional neural networks (CNNs) have been widely applied in remote sensing applications, including land cover classification [9]–[14], scene recognition [15], [16], and image fusion [17]–[20]. In recent years, researchers have also exploited high-level features extracted by CNNs for RSIR and achieved great success [21]–[23].

Once the remote sensing image features have been obtained, a similarity measure is subsequently applied to compute the similarity between query and database images. Most of the existing methods adopt Euclidean distance to measure the similarity. However, it is time-consuming for computing the

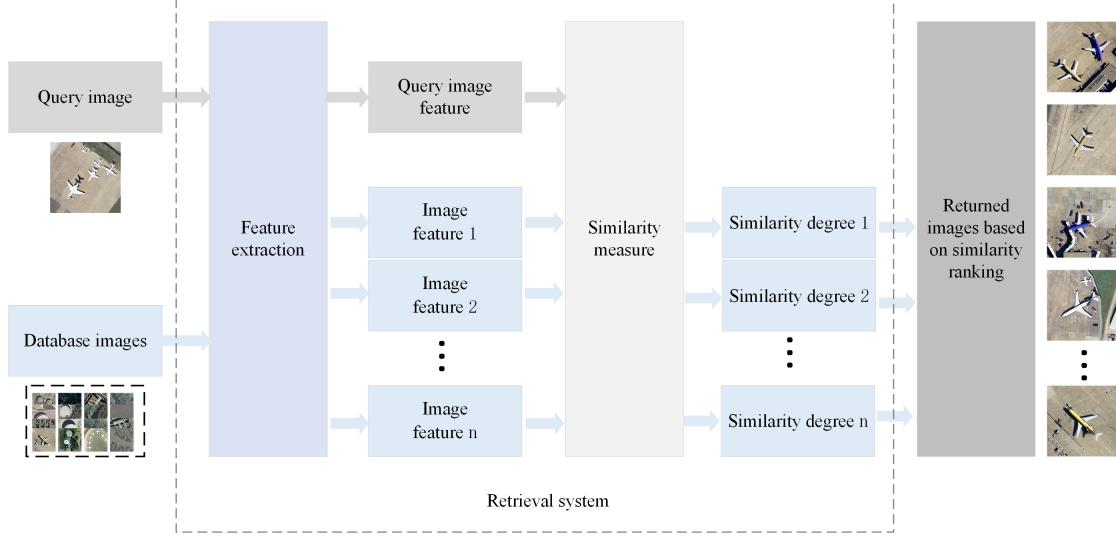


Fig. 1. Illustration of a typical retrieval framework for RSIR.

Euclidean distance between two real-valued features, especially for high-dimensional deep features [24]. In order to solve the above problem, hashing techniques have been largely developed for image retrieval [25], [26]. The main idea behind hashing methods is to learn a set of hash functions that map the high-dimensional image features to low-dimensional hash codes (i.e., binary codes). Different from the complex computation of Euclidean distance, the feature distance between two binary codes (i.e., Hamming distance) can be easily computed via the simple XOR operation.

Recently, deep hashing methods have become the mainstream methods for RSIR. On one hand, deep neural networks are used to extract semantic features for effective content representation. On the other hand, hashing techniques are subsequently adopted to learn binary codes for fast similarity computation. In the past several years, a number of deep hashing methods have been developed for RSIR. For example, Li *et al.* proposed deep hashing neural networks (DHNNs) for large-scale RSIR [27]. Specifically, a pre-trained CNN and a hashing network were exploited to learn high-level semantic features and compact hash codes, respectively. Tang *et al.* embedded hash learning in the generative adversarial framework to ensure the coding balance intuitively [28]. In addition, a cohesion intensive deep hashing model was developed for RSIR, where the cohesiveness of image hash codes within one class was intensified via a weighted loss strategy [29]. In [30], Shan *et al.* combined hash code learning with hard probability sampling in a deep network to improve retrieval performance. In [31], a feature and hash (FAH) learning method, which consists of a deep feature learning model and an adversarial hash learning model, was proposed for RSIR. In [32], Song *et al.* proposed a novel deep hashing network simultaneously for remote sensing image retrieval and classification. The above methods attempt to learn one hash function for both query and database samples in a symmetric way. Specifically, the hash codes of query and database images are all obtained by binarizing the output of the network. However, with the number of database samples

increasing, the training of this kind of symmetric deep hashing networks becomes typically time-consuming.

To achieve fast image retrieval, Jiang *et al.* [33] proposed an asymmetric deep supervised hashing (ADSH) method to generate the hash codes of query and database images in an asymmetric way. In more detail, the hash codes of query images are obtained via the feedback computation of the deep hashing network, while the hash codes of database images are directly learned by solving the designed objective function. Motivated by [33], in this paper, we propose a novel asymmetric hashing method named asymmetric hash code learning (AHCL) for RSIR. Different from ADSH that only considered similarity information between image pairs, we elaborately design a better object function which simultaneously combines the semantic information of each image and similarity information between image pairs to train a deep hashing network in an end-to-end way. By fusing multiple kinds of supervised information in object function, our proposed method can extract the more discriminative deep features to represent the complex remote sensing images. The main contributions of this paper can be summarized as follows:

- A novel asymmetric way is developed to generate hash codes of query and database images, respectively. Compared with the existing symmetric deep hashing approaches, the proposed AHCL can significantly improve the efficiency of generating hash codes. To our knowledge, this is the first time to adopt an asymmetric hashing method for RSIR.
- A loss function is elaborately designed to train the proposed AHCL in an end-to-end way. This loss function combines the semantic loss of each image and similarity loss of pairs of images simultaneously, which improves the representation ability of deep features.
- Comprehensive experiments are performed on three public datasets. The experimental results demonstrate that the proposed AHCL outperforms other competitive deep hashing methods not only in terms of retrieval efficiency

but also in terms of retrieval accuracy.

The remaining parts of this paper are organized as follows. Section II briefly introduces the related work. Section III describes in detail different steps of the proposed method. Comprehensive experiments and discussions are exhibited in Section IV. Finally, conclusions are presented in Section V.

II. RELATED WORK

A. Learning to Hash

Similarity search is a fundamental problem in information retrieval and data mining applications [34]. With the rapid growth of image data, the search time for similar items is typically expensive or impossible. Approximate nearest neighbor (ANN) search has become a hot research topic in recent years. Among ANN techniques, hashing has become one of the most popular and effective techniques due to its encouraging efficiency in both speed and storage. The goal of hashing is to learn a set of hash functions that map the image points from the original space into a Hamming space. Through the hashing transformation, each image is represented by a compact binary code and the similarity in the original space is also preserved. Existing learning to hash methods can be roughly divided into two categories: unsupervised hashing and supervised hashing.

For unsupervised hashing methods, the hash functions are learned from unlabeled training data. Spectral hashing (SH) [35], iterative quantization (ITQ) [36], and density sensitive hashing (DSH) [37] are the typical unsupervised hashing methods. Due to the low capacity of hash codes, unsupervised hashing methods are usually not robust to noise and image transformations. By contrast, supervised hashing methods try to utilize supervised information to learn hash codes. The supervised information can be given in three different forms: point-wise labels, pairwise labels and ranking labels. The representative supervised hashing methods include supervised hashing with kernels (KSH) [38] and sparse embedding and least variance encoding (SELVE) [39]. In addition, a series of deep hashing methods have been developed in the past several years. For example, Xia *et al.* decomposed the hash learning process into a stage of fitting approximate binary codes, followed by a stage of simultaneously fine-tuning the image features and hash functions via a CNN [40]. Li *et al.* adopted pairwise labels information to simultaneously perform feature learning and hash code learning for image retrieval [41]. In addition, Zhang *et al.* utilized pseudo labels to train a deep hashing network in an unsupervised way for scalable image retrieval [42].

B. Deep Hashing in RSIR

Traditional RSIR methods exploit hand-crafted features to represent image content. However, the hand-crafted features cannot accurately describe the semantic information of remote sensing images, which delivers suboptimal retrieval results. With the great progress of deep learning in the computer visual field, combining CNNs with hashing techniques has become the mainstream method of RSIR. In the past several

years, many related algorithms have been developed. For example, Li *et al.* introduced deep hashing neural networks (DHNNs) for single-source RSIR [27] and cross-source RSIR [43], respectively. In [28], a semi-supervised deep adversarial hashing (SDAH) was proposed for large-scale RSIR tasks. In such a work, a residual auto-encoder (RAE) was used to generate the class variable and hash code. Then, two multi-layer networks were constructed to regularize the above vectors. In [30], Shan *et al.* proposed hard probability sampling hash retrieval method to improve retrieval performance. In [31], Liu *et al.* adopted a deep feature learning model and an adversarial hash learning model to extract dense features of images and map the dense features onto the compact hash codes, respectively. In addition, Song *et al.* designed a unified deep-hashing framework to simultaneously achieve retrieval and classification of remote sensing images [32].

III. PROPOSED METHOD

Recently, a large number of deep supervised hashing methods adopt a symmetric way to learn one hash function for both query images and database images. In more detail, the hash codes of all images are generated by binarizing the output of the network. The retrieval phase of this kind of symmetric deep hashing methods is typically time-consuming due to the repeated feedback computation.

To improve the retrieval efficiency, we propose a novel asymmetric deep hashing method for RSIR. Figure 2 presents the schematic of the proposed approach. In the following part, the corresponding procedures are introduced in detail.

A. Deep Feature and Hash Code Extraction

In this section, we construct a deep hashing convolutional neural network (DHCNN) to simultaneously extract deep features and hash codes of remote sensing images [32]. The bottom right of Fig. 2 presents the structure of DHCNN, which mainly consists of three parts. First, a pre-trained deep network is transformed as the backbone network, where the last classification layer is discarded. Note that a number of existing successful deep networks can be used as the backbone network, such as CNN-F [44], AlexNet [45], VGG [46], and ResNet [47]. Then, a new fully connected layer named as the hash layer is built on the backbone network to learn the compact hash codes. Here, we denote K as the size of the hash layer. Finally, another fully connected layer with a softmax activation function, named as the semantic layer, is added after the hash layer to generate the label probability distribution. The size of the semantic layer equals the number of classes in a dataset, which denotes as C .

Let $\mathbf{Q} = \{\mathbf{x}_{q_i}\}_{i=1}^m$ and $\mathbf{D} = \{\mathbf{x}_{d_j}\}_{j=1}^n$ be the query sample dataset and database sample dataset, respectively, where m and n are the number of samples. The corresponding label datasets are represented as $\mathbf{Y}_q = \{\mathbf{y}_{q_i}\}_{i=1}^m$ and $\mathbf{Y}_d = \{\mathbf{y}_{d_j}\}_{j=1}^n$, where \mathbf{y}_{q_i} and \mathbf{y}_{d_j} are the one-hot vectors with the dimension of $C \times 1$. To exploit the supervised information of the labels, the similarity matrix $\mathbf{S} = \{s_{ij}\} \in \{-1, +1\}^{m \times n}$ between the query images and database images can be defined such that $s_{ij} = 1$ if \mathbf{x}_{q_i} and \mathbf{x}_{d_j} come from the same class and $s_{ij} = 0$

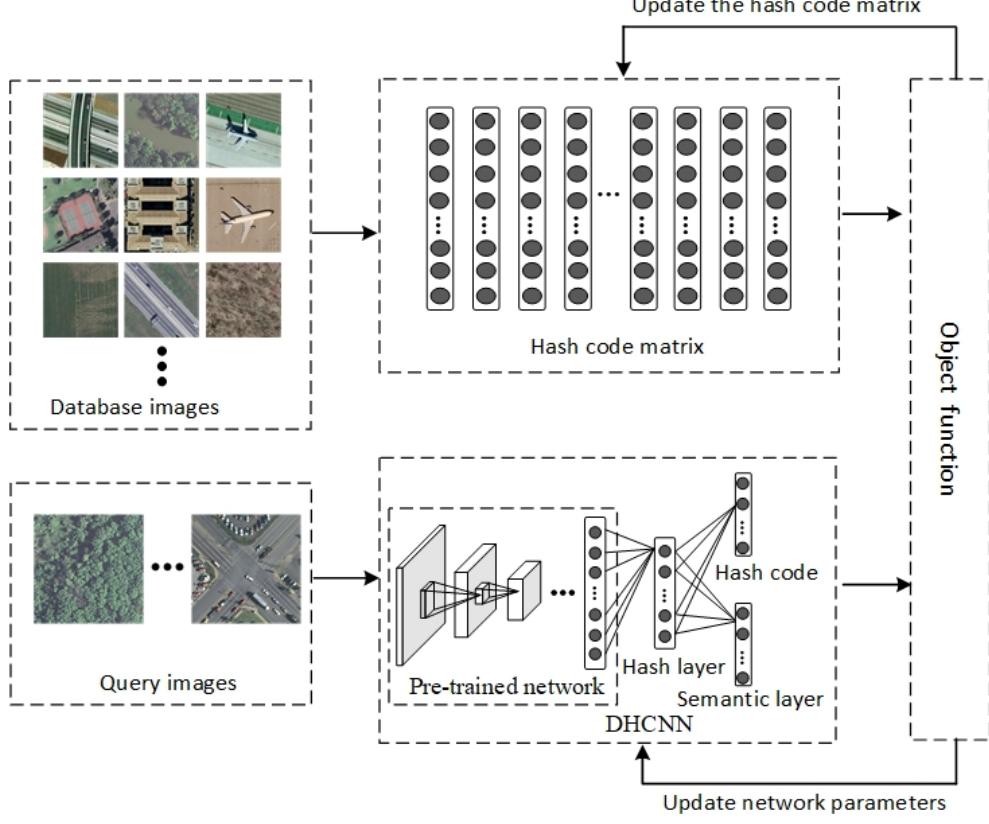


Fig. 2. The flow chart of the proposed AHCL for RSIR.

otherwise. For a query image $\mathbf{x}_{q_i} \in \mathbf{Q}$, we can extract its deep feature (i.e., the output of the backbone network) denoted as \mathbf{f}_{q_i} via the feedback computation of DHCNN

$$\mathbf{f}_{q_i} = \Phi(\mathbf{x}_{q_i}; \theta), i = 1, 2, \dots, m \quad (1)$$

where Φ is the network function characterized by the parameter θ existed in the pre-trained network. This feedback computation actually performs a series of nonlinear and linear transformations, including convolution, pooling, and nonlinear mapping. Then, the high-dimensional deep feature is mapped to low-dimensional hash code with K bits via binarizing the output of the hash layer, which can be represented as:

$$\mathbf{b}_{q_i} = sign(\mathbf{u}_{q_i}) \quad (2)$$

where $\mathbf{u}_{q_i} = \mathbf{W}_h \mathbf{f}_{q_i} + \mathbf{v}_h$ refers to a hash-like code, $\mathbf{W}_h \in \mathbb{R}^{K \times 4096}$ and $\mathbf{v}_h \in \mathbb{R}^{K \times 1}$ denote the weight matrix and bias vector of the hash layer, respectively. Here, $sign(\cdot)$ performs an element-wise operation for a matrix or a vector, i.e., $sign(x) = 1$ if $x > 0$ and -1 otherwise.

B. Loss Function Definition

Due to the complex imaging condition, there exist large intraclass and low interclass variabilities in remote sensing images. To this end, we adopt the product loss between the

query images and database images to learn the similarity-preserving deep features, which can be defined as:

$$\mathcal{L}_1(\mathbf{B}_q, \mathbf{B}_d) = \sum_{i=1}^m \sum_{j=1}^n (\mathbf{b}_{q_i}^T \mathbf{b}_{d_j} - K s_{ij})^2 \quad (3)$$

where $\mathbf{B}_q = \{\mathbf{b}_{q_i}\}_{i=1}^m \in \{-1, +1\}^{m \times K}$ and $\mathbf{B}_d = \{\mathbf{b}_{d_j}\}_{j=1}^n \in \{-1, +1\}^{n \times K}$ represent the hash code matrixes of query image dataset \mathbf{Q} and database image dataset \mathbf{D} , respectively. As mentioned above, the hash codes of query images is obtained by DHCNN. Thus, the above Equation (3) can be rewritten as:

$$\mathcal{L}_2(\mathbf{B}_q, \mathbf{B}_d) = \sum_{i=1}^m \sum_{j=1}^n [sign(\mathbf{W}_h \Phi(\mathbf{x}_{q_i}; \theta) + \mathbf{v}_h)^T \mathbf{b}_{d_j} - K s_{ij}]^2. \quad (4)$$

Since the sign function is not derivable, the gradient cannot be prorogated to the former layers of DHCNN. To this end, we adopt the hyperbolic tangent function to approximate the sign function, i.e.:

$$\mathcal{L}_3(\mathbf{B}_q, \mathbf{B}_d) = \sum_{i=1}^m \sum_{j=1}^n [\tanh(\mathbf{W}_h \Phi(\mathbf{x}_{q_i}; \theta) + \mathbf{v}_h)^T \mathbf{b}_{d_j} - K s_{ij}]^2. \quad (5)$$

In most cases, the query dataset is randomly sampled from the database dataset, i.e., $\mathbf{B}_q = \mathbf{B}_d^\Omega$, where \mathbf{B}_d^Ω refers to the

dataset indicated by the index set Ω . Here, let $\Gamma = \{1, 2, \dots, n\}$ and $\Omega = \{i_1, i_2, \dots, i_m\} \in \Gamma$ be the database sample index set and query sample index set, respectively. Based on the above definition, the loss function is rewritten as:

$$\mathcal{L}_4(\mathbf{B}_q, \mathbf{B}_d) = \sum_{i \in \Omega} \sum_{j \in \Gamma} [\tanh(\mathbf{W}_h \Phi(\mathbf{x}_{d_i}; \theta) + \mathbf{v}_h)^T \mathbf{b}_{d_j} - K s_{ij}]^2. \quad (6)$$

Considering that $\Omega \in \Gamma$, there are two representation ways of the hash code for query image \mathbf{x}_{d_i} . The one is the element of database hash code matrix, i.e., \mathbf{b}_{d_i} ; the other is the hash-like code (i.e., the output of the hash layer) $\tilde{\mathbf{u}}_{d_i} = \tanh(\mathbf{u}_{d_i})$, where $\mathbf{u}_{d_i} = \mathbf{W}_h \Phi(\mathbf{x}_{d_i}; \theta) + \mathbf{v}_h$. Based on the above analysis, the designed loss function should consider the approximation error. Thus, we add an extra constraint in Equation (6) to make the above two representation ways be as close as possible, i.e.:

$$\begin{aligned} \mathcal{L}_5(\mathbf{B}_q, \mathbf{B}_d) &= \sum_{i \in \Omega} \sum_{j \in \Gamma} (\tilde{\mathbf{u}}_{d_i}^T \mathbf{b}_{d_j} - K s_{ij})^2 \\ &\quad + \lambda \sum_{i \in \Omega} [\mathbf{b}_{d_i} - \tilde{\mathbf{u}}_{d_i}]^2 \end{aligned} \quad (7)$$

where λ is a hyper-parameter which is used to constrain the representation error.

Equation (7) exploits the similarity information between image pairs to learn similarity-preserving deep features. By minimizing Equation (7), images from the same classes should be encoded as closely as possible and images from the different classes should be encoded far from each other in the feature space. However, apart from information on the similarity between images, each image has its own rich semantic information. To improve the representation ability of features, the semantic information should be considered in the designed loss function. First, the class probability distribution can be computed via the semantic layer with a softmax activation function, i.e.:

$$\mathbf{t}_{d_i} = \text{softmax}(\mathbf{W}_s \mathbf{u}_{d_i} + \mathbf{v}_s), \quad i \in \Omega \quad (8)$$

where $\mathbf{W}_s \in \mathbb{R}^{C \times K}$ and $\mathbf{v}_s \in \mathbb{R}^{C \times 1}$ refer to the weight matrix and bias vector of the semantic layer, respectively. Finally, the cross-entropy loss function is used to minimize the error between the predicted label and the ground-truth label and further added into Equation (7). The final loss function is rewritten as:

$$\begin{aligned} \mathcal{L}_6(\mathbf{B}_q, \mathbf{B}_d) &= \sum_{i \in \Omega} \sum_{j \in \Gamma} (\tilde{\mathbf{u}}_{d_i}^T \mathbf{b}_{d_j} - K s_{ij})^2 \\ &\quad + \lambda \sum_{i \in \Omega} (\mathbf{b}_{d_i} - \tilde{\mathbf{u}}_{d_i})^2 + \gamma \left(\sum_{i \in \Omega} -\mathbf{y}_{d_i} \log \mathbf{t}_{d_i} \right) \end{aligned} \quad (9)$$

where γ is a hyper-parameter which is used to balance the similarity loss and semantic loss.

In Equation (9), the first term is used to preserve the similarity information between images. The second term constrains the approximation error between two representation ways of hash codes of query images. The third term considers the semantic loss of each image between the predicted label and ground-truth label.

C. Objective Function Solving

After defining the loss function, the objective function can be written as:

$$\begin{aligned} \mathcal{J} = \min_{\Theta, \mathbf{B}_d} \mathcal{L}_6 &= \min \left\{ \sum_{i \in \Omega} \sum_{j \in \Gamma} (\tilde{\mathbf{u}}_{d_i}^T \mathbf{b}_{d_j} - K s_{ij})^2 \right. \\ &\quad \left. + \lambda \sum_{i \in \Omega} (\mathbf{b}_{d_i} - \tilde{\mathbf{u}}_{d_i})^2 + \gamma \left(\sum_{i \in \Omega} -\mathbf{y}_{d_i} \log \mathbf{t}_{d_i} \right) \right\}. \end{aligned} \quad (10)$$

In the above objective function, the variables need to be learned including network parameter $\Theta = \{\theta, \mathbf{W}_h, \mathbf{v}_h, \mathbf{W}_s, \mathbf{v}_s\}$ and database hash code matrix \mathbf{B}_d . Motivated by [33], we adopt an alternating optimization algorithm to learn the above two variables. More specifically, we solve one variable with the other one fixed. The specific procedures are as follows.

1) *Solve Θ with \mathbf{B}_d fixed*: In order to clearly present the solving process, this section deduces the gradient of the objective function to the parameters of the semantic layer (i.e., \mathbf{W}_s and \mathbf{v}_s), the parameters of the hash layer (i.e., \mathbf{W}_h and \mathbf{v}_h), and the parameters of the pre-trained network (i.e., θ) in turn. First, the partial derivative of the objective function with respect to the predicted class distribution \mathbf{t}_{d_i} is calculated:

$$\frac{\partial \mathcal{J}}{\partial \mathbf{t}_{d_i}} = \frac{\partial \mathcal{L}_6}{\partial \mathbf{t}_{d_i}} = -\gamma \frac{\mathbf{y}_{d_i}}{\mathbf{t}_{d_i}}. \quad (11)$$

Then the gradient of the objective function with respect to the parameters of the semantic layer can be calculated:

$$\frac{\partial \mathcal{J}}{\partial \mathbf{W}_s} = \frac{\partial \mathcal{J}}{\partial \mathbf{t}_{d_i}} \frac{\partial \mathbf{t}_{d_i}}{\partial \mathbf{o}_{d_i}} \frac{\partial \mathbf{o}_{d_i}}{\partial \mathbf{W}_s} = \frac{\partial \mathcal{J}}{\partial \mathbf{t}_{d_i}} \odot \mathbf{t}_{d_i} \odot (\mathbf{y}_{d_i} - \mathbf{t}_{d_i}) \mathbf{u}_{d_i}^T \quad (12)$$

$$\frac{\partial \mathcal{J}}{\partial \mathbf{v}_s} = \frac{\partial \mathcal{J}}{\partial \mathbf{t}_{d_i}} \frac{\partial \mathbf{t}_{d_i}}{\partial \mathbf{o}_{d_i}} \frac{\partial \mathbf{o}_{d_i}}{\partial \mathbf{v}_s} = \frac{\partial \mathcal{J}}{\partial \mathbf{t}_{d_i}} \odot \mathbf{t}_{d_i} \odot (\mathbf{y}_{d_i} - \mathbf{t}_{d_i}) \quad (13)$$

where $\mathbf{o}_{d_i} = \mathbf{W}_s \mathbf{u}_{d_i} + \mathbf{v}_s$, the operator \odot represents an element-by-element multiplication. Furthermore, the partial derivative of the objective function with respect to \mathbf{u}_{d_i} can be represented as:

$$\begin{aligned} \frac{\partial \mathcal{J}}{\partial \mathbf{u}_{d_i}} &= \left\{ [2 \sum_{j \in \Gamma} (\tilde{\mathbf{u}}_{d_i}^T \mathbf{b}_{d_j} - K s_{ij}) \mathbf{b}_{d_j}] + 2\lambda [\mathbf{b}_{d_i} - \tilde{\mathbf{u}}_{d_i}] \right\} \\ &\quad \odot (1 - \tilde{\mathbf{u}}_{d_i}^2) + \gamma (-\mathbf{W}_s^T (\mathbf{y}_{d_i} - \mathbf{t}_{d_i})). \end{aligned} \quad (14)$$

After obtaining the above partial derivatives, the gradient of the objective function with respect to the parameters of the hash layer is further calculated, i.e.:

$$\frac{\partial \mathcal{J}}{\partial \mathbf{W}_h} = \frac{\partial \mathcal{J}}{\partial \mathbf{u}_{d_i}} \frac{\partial \mathbf{u}_{d_i}}{\partial \mathbf{W}_h} = \frac{\partial \mathcal{J}}{\partial \mathbf{u}_{d_i}} \mathbf{f}_{d_i}^T \quad (15)$$

$$\frac{\partial \mathcal{J}}{\partial \mathbf{v}_h} = \frac{\partial \mathcal{J}}{\partial \mathbf{u}_{d_i}} \frac{\partial \mathbf{u}_{d_i}}{\partial \mathbf{v}_h} = \frac{\partial \mathcal{J}}{\partial \mathbf{u}_{d_i}}. \quad (16)$$

Finally, the gradient of the objective function with respect to the parameters of the pre-trained network is also calculated:

$$\begin{aligned} \frac{\partial \mathcal{J}}{\partial \theta} &= \frac{\partial \mathcal{J}}{\partial \mathbf{u}_{d_i}} \frac{\partial \mathbf{u}_{d_i}}{\partial \Phi(\mathbf{x}_{d_i}; \theta)} \frac{\partial \Phi(\mathbf{x}_{d_i}; \theta)}{\partial \theta} \\ &= \mathbf{W}_h^T \frac{\partial \mathcal{J}}{\partial \mathbf{u}_{d_i}} \frac{\partial \Phi(\mathbf{x}_{d_i}; \theta)}{\partial \theta}. \end{aligned} \quad (17)$$

When the gradients of all parameters are obtained, the standard gradient descent algorithm (SGD) is used to update all parameters, i.e.:

$$\xi = \xi - \mu \frac{\partial \mathcal{J}}{\partial \xi}, \xi = \mathbf{W}_s, \mathbf{W}_h, \mathbf{v}_s, \mathbf{v}_h, \theta \quad (18)$$

where μ refers to the learning rate.

2) *Solve \mathbf{B}_d with Θ fixed:* When Θ is fixed, Equation (10) can be rewritten in a matrix form, i.e.:

$$\begin{aligned} \mathcal{J} = \min_{\mathbf{B}_d} \mathcal{L}_6 &= \min_{\mathbf{B}_d} \{ \| \tilde{\mathbf{U}}_d \mathbf{B}_d^T - K \mathbf{S} \|^2_F \\ &\quad + \lambda \| \mathbf{B}_d^\Omega - \tilde{\mathbf{U}}_d \|^2_F + \gamma (-\mathbf{Y}_d \log \mathbf{T}_d) \} \\ &= \min_{\mathbf{B}_d} \{ \| \tilde{\mathbf{U}}_d \mathbf{B}_d^T \|^2_F - 2K \text{tr}(\mathbf{B}_d^T \mathbf{S}^T \tilde{\mathbf{U}}_d) \\ &\quad - 2\lambda \text{tr}(\mathbf{B}_d^\Omega \tilde{\mathbf{U}}_d^T) + \text{const} \}. \end{aligned} \quad (19)$$

where $\tilde{\mathbf{U}}_d$, \mathbf{B}_d , \mathbf{S} , \mathbf{Y}_d , and \mathbf{T}_d are the matrix form of the corresponding variables. \mathbf{B}_d^Ω denotes the hash code matrix for the samples in the database indexed by Ω . “const” represents a constant independent of \mathbf{B}_d . After that, we define a new variable $\bar{\mathbf{U}}_d = \{\bar{\mathbf{u}}_{d_j}\}_{j=1}^n$, i.e.:

$$\bar{\mathbf{u}}_{d_j} = \begin{cases} \tilde{\mathbf{u}}_{d_j}, & \text{if } j \in \Omega \\ 0, & \text{otherwise.} \end{cases} \quad (20)$$

Thus, Equation (19) can be rewritten as:

$$\begin{aligned} \mathcal{J} &= \min_{\mathbf{B}_d} \{ \| \mathbf{B}_d \tilde{\mathbf{U}}_d^T \|^2_F - 2 \text{tr}(\mathbf{B}_d [K \tilde{\mathbf{U}}_d^T \mathbf{S} + \lambda \bar{\mathbf{U}}_d]^T) + \text{const} \} \\ &= \min_{\mathbf{B}_d} \{ \| \mathbf{B}_d \tilde{\mathbf{U}}_d^T \|^2_F + \text{tr}(\mathbf{B}_d \mathbf{Q}_d^T) + \text{const} \} \end{aligned} \quad (21)$$

where $\mathbf{Q}_d = -2K \mathbf{S}^T \mathbf{B}_d \tilde{\mathbf{U}}_d - 2\lambda \bar{\mathbf{U}}_d$.

Based on the above definition, we learn the whole \mathbf{B}_d by updating one column of \mathbf{B}_d successively and fixing the other columns. Assume that $\mathbf{B}_{d_{*k}}$, $\tilde{\mathbf{U}}_{d_{*k}}$, and $\mathbf{Q}_{d_{*k}}$ are the k th columns of \mathbf{B}_d , $\tilde{\mathbf{U}}_d$, and \mathbf{Q}_d , respectively, and that $\hat{\mathbf{B}}_{d_k}$, $\hat{\mathbf{U}}_{d_k}$, and $\hat{\mathbf{Q}}_{d_k}$ are the matrices of \mathbf{B}_d , $\tilde{\mathbf{U}}_d$, and \mathbf{Q}_d excluding the k th columns, respectively. The objective function can be further rewritten as:

$$\begin{aligned} \mathcal{J} &= \min_{\mathbf{B}_{d_{*k}}} \{ \| \mathbf{B}_d \tilde{\mathbf{U}}_d^T \|^2_F + \text{tr}(\mathbf{B}_d \mathbf{Q}_d^T) + \text{const} \} \\ &= \min_{\mathbf{B}_{d_{*k}}} \{ \text{tr}(\mathbf{B}_{d_{*k}} [2 \tilde{\mathbf{U}}_{d_{*k}}^T \hat{\mathbf{U}}_{d_k} \hat{\mathbf{B}}_{d_k}^T + \mathbf{Q}_{d_{*k}}^T]) + \text{const} \}. \end{aligned} \quad (22)$$

By solving Equation (22), we can gradually update $\mathbf{B}_{d_{*k}}$, i.e.:

$$\mathbf{B}_{d_{*k}} = -\text{sign}(2 \hat{\mathbf{B}}_{d_k} \hat{\mathbf{U}}_{d_k}^T \tilde{\mathbf{U}}_{d_{*k}} + \mathbf{Q}_{d_{*k}}). \quad (23)$$

After training, for a unseen query image \mathbf{f}_{q_i} , its hash code is obtained by using the following equation:

$$\mathbf{b}_{q_i} = \text{sign}(\mathbf{u}_{q_i}) = \text{sign}(\mathbf{W}_h \Phi(\mathbf{x}_{q_i}; \theta) + \mathbf{v}_h). \quad (24)$$

IV. EXPERIMENTS

To verify the effectiveness of the proposed method for RSIR, we compare the proposed AHCL against some state-of-the-art methods on three public remote sensing image datasets. In the following part, Section IV-A introduces the used datasets. Section IV-B describes the experimental settings. Section IV-C reports the experimental results. Section IV-F discusses the effects of two important parameters of the proposed method on retrieval results.

A. Datasets

We select three remote sensing image datasets to conduct RSIR experiments. The detailed descriptions of these datasets are as follows:

- The first dataset is the University of California, Merced dataset (UCMD) [48] which was extracted from the United States Geological Survey (USGS). It contains 21 land cover categories and each category includes 100 images. The size of the images is 256×256 , and the spatial resolution of each pixel is 0.3 m. Some examples of different scenes are presented in Fig. 3.
- The second dataset is the WHU-RS dataset [49] which was collected from Google Earth. The images are divided into 19 classes, each class has approximately 50 images with 600×600 pixels. Some examples of different scenes are presented in Fig. 4.
- The third dataset is the aerial image dataset (AID) [50] which was collected with the goal of advancing the state-of-the-art for the scene classification of remote sensing images. The dataset has a number of 10000 images within 30 classes. Each class consists of 220 to 420 images of size of 600×600 pixels. Some examples of different scenes are presented in Fig. 5.

For UCMD, WHU-RS, and AID datasets, we randomly select 80%, 50%, and 50% of the labeled samples per class as training samples, respectively, the rest of the samples are regarded as the test set.

B. Experimental Settings

To extract remote sensing image deep features, we adopt VGG11 [46] as the pre-trained network (i.e., backbone network), which includes eight convolutional layers and three fully connected layers. In experiments, the last classification layer of VGG11 is discarded. We systematically compare our method with some traditional hashing methods and deep hashing methods. The traditional methods include SELVE [39] and KSH [38]. The deep hashing methods include deep pairwise-supervised hashing (DPSH) [41], and DHNNs with the L2 regularization (DHNNs-L2) [27], asymmetric deep supervised hashing (ADSH) [33], FAH [31], and DHCNN [32]. In addition, another approach named graph relation network with scalable neighbor discriminative loss with binary cross entropy (GRN-SNDL-BCE) [23] is also regarded as baseline. For traditional methods, each remote sensing image is represented by 4096-dimensional CNN features extracted from the penultimate layer of VGG11. For deep hashing methods, all images are first resized to be of 224×224 pixels and then directly fed into the deep networks. The parameters of the compared methods are set to default values according to the original papers. For our proposed AHCL method, the parameters λ and γ are set to 200 and 20, respectively. All experiments are performed on a computer equipped with an Intel Core i7-9700 with 3.0 GHz, 64G memory, and an NVIDIA GeForce RTX 2060 SUPER GPU.

To evaluate the performance of the retrieval methods, we adopt four metrics, i.e., Mean Average Precision (MAP), Pre-



Fig. 3. Examples of different scenes in the UCMD.

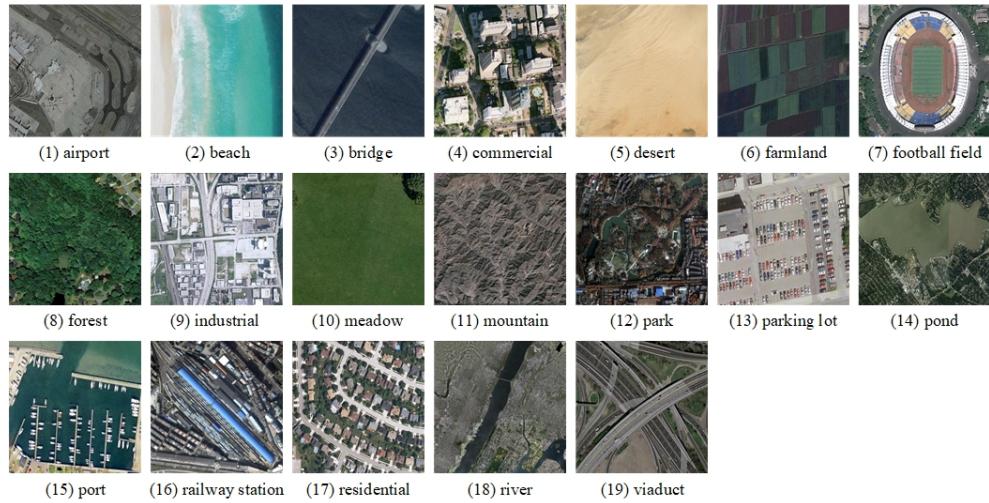


Fig. 4. Examples of different scenes in the WHU-RS.



Fig. 5. Examples of different scenes in the AID.

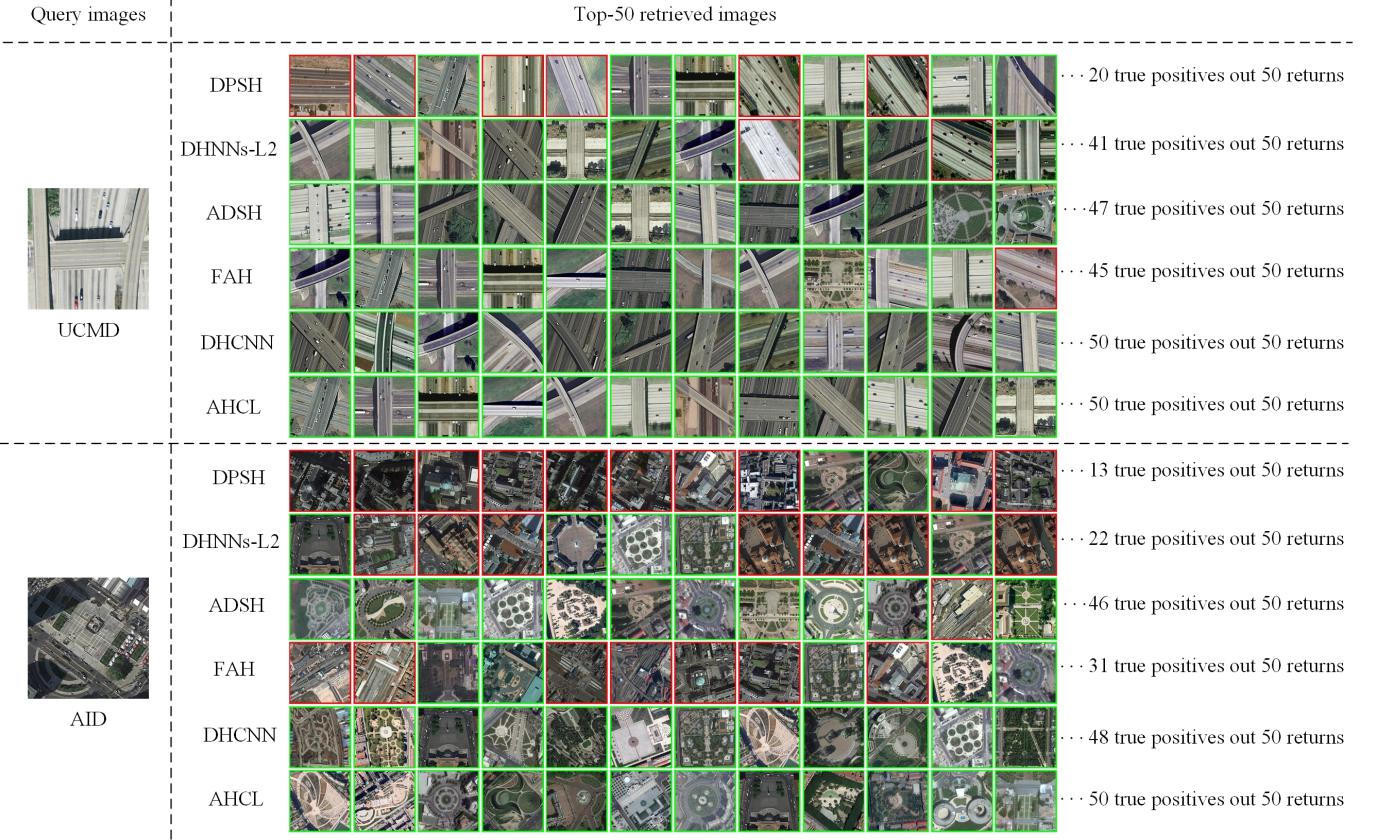


Fig. 6. The query examples with the top-50 retrieved images on the UCMD and AID datasets, where the green rectangle marks the true positives and the red rectangle marks the false positives.

cision@ k , Recall@ k , and Precision-Recall. The descriptions of these metrics are as follows:

- MAP: In the query phase, we firstly rank all database samples in ascending order by computing the Hamming distance between the query sample and the database samples. Once obtaining the ranked list, we can get the average precision (AP) for each query image. Finally, the MAP can be computed via averaging the AP of all query images, which is defined as:

$$\text{MAP} = \frac{1}{|Q|} \sum_{i=1}^{|Q|} \frac{1}{n_i} \sum_{j=1}^{n_i} P(i, j) \quad (25)$$

where $|Q|$ is the volume of the query image set, n_i is the number of images relevant to i th query image in the searching database, and $P(i, j)$ is the precision of the top j th retrieved image of i th query image.

- Precision@ k : This metric measures the precision value of the top k retrieved images, which is defined as:

$$\text{Precision}@k = \frac{n}{k} \quad (26)$$

where k and n are the numbers of all images and similar images to the query image in the top k list, respectively.

- Recall@ k : Recall@ k computes the recall rate between the number of similar images to the query image in the top

k retrieved image and all similar images in the database, which is defined as:

$$\text{Recall}@k = \frac{n}{r} \quad (27)$$

where r and n are the number of similar images in the database and the top k retrieved images, respectively.

- Precision-Recall: The Precision-Recall metric is another popular evaluation protocol in image retrieval, which plots the precision and recall rates at different searching Hamming radius. The first point of the Precision-Recall curve represents the precision and recall rate at the Hamming radius equals 0; the next point means the precision and recall rate at the Hamming radius equals 1, and so on.

C. Retrieval Results

In the first place, we compare the proposed AHCL with five competitive deep hashing methods, including DPSH, DHNNs-L2, ADSH, FAH, and DHCNN, in terms of qualitative retrieval results. Fig. 6 presents query examples with the top-50 retrieved images on the UCMD and AID datasets, where the green rectangle marks the true positives and the red rectangle marks the false positives. Due to the limitation of space, we only visually show the top-12 retrieved images and count the number of true positives out 50 returns. From this figure, we can see that DPSH obtains the worse result

TABLE I
IMAGE RETRIEVAL RESULTS IN TERMS OF MAP WITH 16, 32, AND 64 HASH BITS ON THE THREE DATASETS. NOTE THAT GRN-SNDL-BCE [?] IS NOT HASHING-BASED METHOD, WE SET THE LENGTH OF FEATURE TO 64 FOR COMPARISON.

Methods	UCMD			WHU-RS			AID		
	16 bits	32 bits	64 bits	16 bits	32 bits	64 bits	16 bits	32 bits	64 bits
AHCL (Our method)	0.9709	0.9762	0.9854	0.9661	0.9811	0.9843	0.8990	0.9537	0.9559
DHCNN [32]	0.9682	0.9718	0.9822	0.9412	0.9694	0.9743	0.8935	0.9457	0.9502
GRN-SNDL-BCE [23]	-	-	0.9833	-	-	0.9808	-	-	0.9506
FAH [31]	0.9010	0.9561	0.9653	0.7776	0.9508	0.9649	0.8494	0.9248	0.9281
ADSH [33]	0.9651	0.9689	0.9810	0.9334	0.9494	0.9739	0.8898	0.9472	0.9493
DHNNs-L2 [27]	0.9232	0.9569	0.9649	0.8923	0.9243	0.9502	0.8239	0.8632	0.9221
DPSH [41]	0.8382	0.9135	0.9225	0.7245	0.7941	0.8532	0.7532	0.8037	0.8822
KSH-CNN [38]	0.7755	0.8475	0.8792	0.6953	0.7532	0.8073	0.5043	0.6053	0.6531
SELVE-CNN [39]	0.3863	0.4254	0.4308	0.4238	0.4929	0.5032	0.3508	0.3907	0.3840

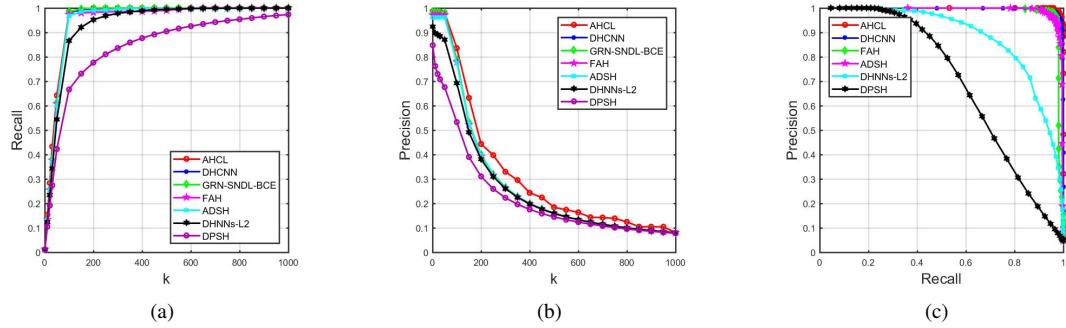


Fig. 7. The retrieval results on UCMD with 64-bit hash code. (a) Recall@k; (b) Precision@k; (c) Precision-Recall.

results, DHNNs-L2 and FAH perform good for the simple scene (e.g., overpass of UCMD dataset) but perform bad for the complex class (e.g., square of AID dataset). In addition, we also observe that ADSH and DHCNN obtain the competitive retrieval results, but there still exist several false positives in their retrieved images. By contrast, the proposed AHCL returns all true positives for the two examples, which demonstrates the advantages of our method over other compared approaches. In addition, the quantitative retrieval results in terms of MAP are also reported. Table I shows the MAP of different methods with different hash bits on the three datasets. Considering that GRN-SNDL-BCE is not hashing method, we set the length of feature to 64 and compare it with other hashing approaches with 64 hash bits. From this table, we can obtain the following conclusions: (1) the length of hash codes has a great influence on the retrieval results, and the retrieval performance with short hash bits is generally suboptimal due to their insufficient representation ability; (2) the deep hashing methods are significantly superior to the traditional hashing methods with deep features; (3) by fusing the similarity information and semantic information, the proposed AHCL delivers the better retrieval results than ADSH; (4) GRN-SNDL-BCE obtains the competitive retrieval results, the main reason is the relations between samples are well excavated via a graph relation network and a designed loss function. In addition, GRN-SNDL-BCE adopts the more powerful backbone architecture (i.e., ResNet18 [47]) than our pre-trained network (i.e., VGG11 [46]); (5) the proposed AHCL obtains the highest MAP values with different hash bits on three datasets.

Apart from the MAP metric, we also report other three important metrics, i.e., Recall@k, Precision@k, and Precision-Recall curves. In this part, we exclude the traditional hashing methods with deep features (i.e., KSH-CNN [38] and SELVE-CNN [39]) due to their poor performance. In addition, considering that the Precision-Recall curves are based on Hamming radius in this paper, thus, the Precision-Recall curve of GRN-SNDL-BCE is not compared with others. Figs.7-9 show the corresponding retrieval results of different methods on the three datasets, where the hash bit is set to 64. As can be seen from Figs. 7-9, DPSH and DHNNs-L2 show poor retrieval performance. On the contrary, other methods have achieved satisfactory retrieval results. In addition, the proposed AHCL method has obtained the higher retrieval values than other compared methods in most cases.

D. Effects of Different Training Samples on MAP

In this section, we conduct experiments to analyze the effect of different number of training samples on retrieval result under 64-bit hash codes. Here, we only compare the proposed AHCL with GRN-SNDL-BCE [23], FAH [31], ADSH [33], and DHNNs-L2 [27], the rest of compared approaches are excluded due to the poor retrieval results obtained by these methods. The ratio between training and all samples are set to 0.2, 0.4, 0.6, and 0.8 for three datasets.

The retrieval results in terms of MAP are shown in Fig. 12. From this figure, we can see that DHNNs-L2 is very sensitive to the number of training samples. When small amount of training samples are available, the retrieval results of DHNNs-L2 on three datasets dramatically decrease. By contrast, the

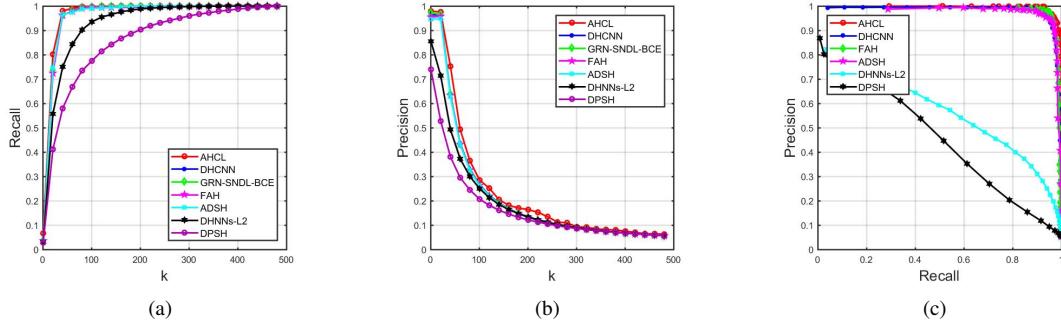


Fig. 8. The retrieval results on WHU-RS with 64-bit hash code. (a) Recall@k. (b) Precision@k. (c) Precision-Recall.

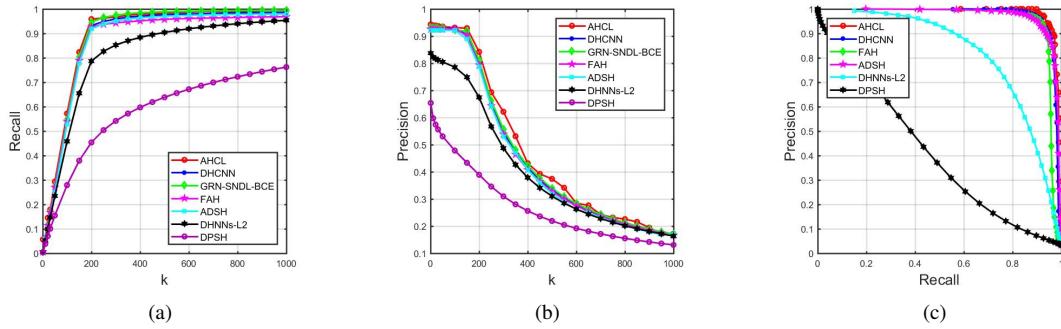


Fig. 9. The retrieval results on AID with 64-bit hash code. (a) Recall@k. (b) Precision@k. (c) Precision-Recall.

TABLE II
COMPARISON OF RUNNING TIME (IN SECONDS) OF DIFFERENT METHODS.

Methods	16 bits		32 bits		64 bits	
	Training time	Retrieval time	Training time	Retrieval time	Training time	Retrieval time
AHCL (Our method)	1243.52	24.17	1244.45	24.09	1249.75	24.26
DHCNN [32]	1064.56	67.69	1067.45	70.43	1071.78	72.85
ADSH [33]	1237.29	24.21	1239.25	24.57	1244.95	24.28
DHNNs-L2 [27]	1049.56	69.49	1045.45	74.57	1058.78	78.32
DPSH [41]	1047.20	75.05	1049.45	75.04	1056.78	78.76

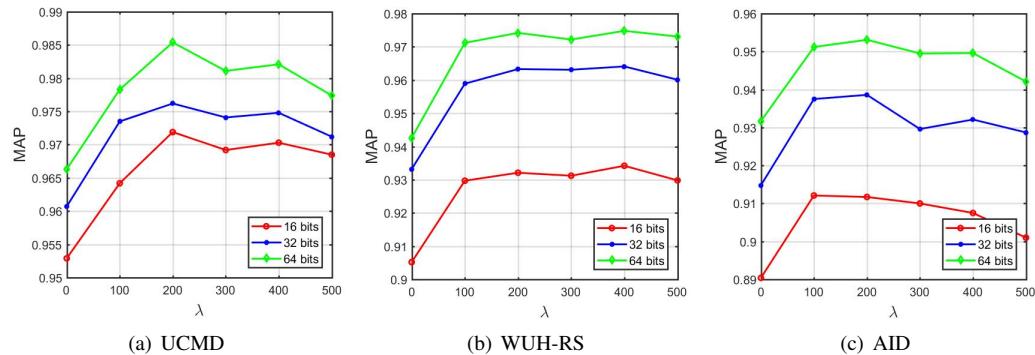


Fig. 10. The effects of λ on MAP

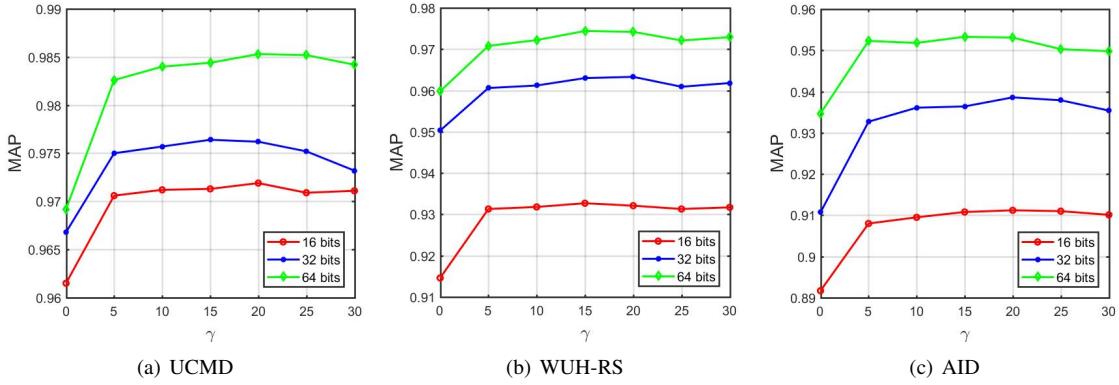


Fig. 11. The effects of γ on MAP

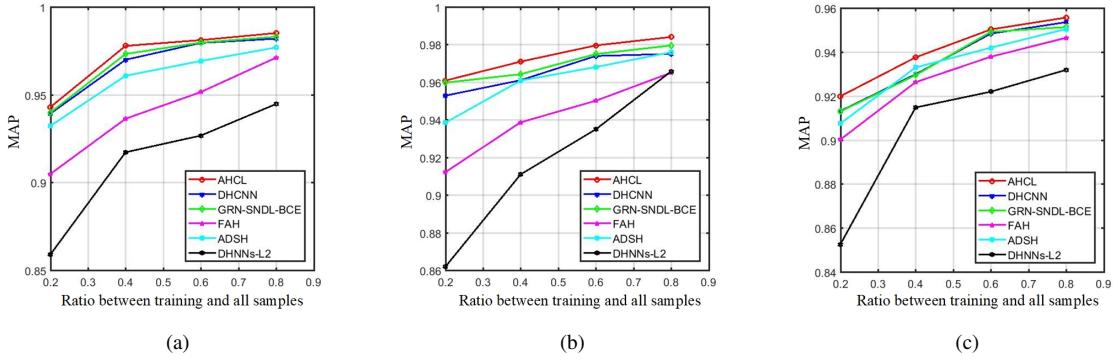


Fig. 12. The retrieval results under different number of training samples on the (a) UCMD, (b) WHU-RS, and (c) AID.

MAP values of other methods steadily rise with the number of training samples increasing. Although DHCNN and GRN-SNDL-BCE obtain the competitive results, we can still see that the proposed AHCL delivers the highest MAP values for all separation scenarios on three datasets. Based on the above analyses, we can conclude that the proposed AHCL can achieve satisfactory retrieval performance under different separation scenarios of samples, and at the same time, exhibit advantage over other compared methods to some extent.

E. Computing Time

In addition to the quantitative metrics, retrieval efficiency is also an important factor when designing a retrieval algorithm. Thus, we further compare the proposed AHCL method with four deep hashing methods in terms of running time. The experiments are performed on the AID dataset and the training ratio is set to 0.5 per class. Table II shows the comparison of the training and retrieval time of different methods with 16, 32, and 64 hash bits. From this table, we can see that the training time of DHCNN is slightly higher than that of DHNNs-L2 and DPSH. At the same time, the proposed AHCL also takes more training time than that of ADSH. The main reason for the above experimental phenomenon is that AHCL and DHCNN add a semantic layer after the hash layer to consider the semantic information of images. Therefore, these two methods need more time to train the additional parameter layer. In addition, we can also observe that the retrieval time of the AHCL and ADSH methods is much lower than that

of other three symmetric hashing methods, which verifies the efficiency of the asymmetric strategy for hash code learning.

F. Parameter Analysis

As can be seen from Equation (10), the proposed AHCL method contains two important hyper-parameters, i.e., λ and γ . The variable λ is used to constrain the representation error between two hash code representations for query images. The variable γ is used to balance the similarity loss and semantic loss. In the following parts, the effects of the above two hyper-parameters on MAP values are analyzed in detail.

1) *The effects of λ on MAP:* In order to analyze the effect of λ on the retrieval performance, the γ value is set to 20 according to experience [32]. Figure 10 shows the changing curve of the MAP values with the increase of λ on the UCMD, WHU-RS, and AID datasets, where the hash bits K are set to 16, 32 and 64, respectively. As can be seen from this figure, when the hash bit K increases, the MAP values improve significantly. In addition, when $\lambda = 0$, MAP values reach the lowest value, the main reason is that the objective function cannot effectively constrain the approximation error between the hash-like codes and the hash codes to be enough small. For both UCMD and AID datasets, the best MAP values are achieved when $\lambda = 200$ for all hash bits. Although for the WHU-RS dataset, the MAP values under $\lambda = 200$ do not reach the maximum values, the results at this time are still very close to the maximum values. Thus, we set $\lambda = 200$ as the optimal value for the three datasets.

2) *The effects of γ on MAP:* Before analyzing the effects of γ on MAP, the λ value is set to 200 for all three datasets. Fig. 11 shows the effects of γ on the MAP values. From this figure, we can see that when γ approaches to 0, the MAP values significantly decrease for all scenarios. The main reason for the above experimental phenomenon is that objective function under the condition of $\gamma = 0$ only considers the similar information between images, while ignoring the semantic information of each image. When $\gamma > 0$, the MAP values increase significantly and become stable with the increase of γ . Through the above observation, it is found that the proposed method can obtain satisfactory retrieval results on all datasets when γ equals 20.

V. CONCLUSIONS

Currently, deep hashing-based RSIR methods attempt to learn one hash function for both query and database samples in a symmetric way. Specifically, the hash codes of query and database remote sensing images are all obtained by binarizing the output of the network. However, it is typically time-consuming to generate the hash codes of huge database images. To this end, we proposed a novel asymmetric deep hashing method for fast RSIR. In more detail, the hash codes of query images are obtained via the feedback computation of the deep hashing network, while the hash codes of database images are directly learned by solving the objective function. The proposed asymmetric strategy improves the generation efficiency of hash codes, which is vital for the large-scale retrieval task. In addition, the designed loss function simultaneously exploits the semantic information and similarity information of images to enhance the ability of feature representation. Finally, the experimental results validate the superiority of the proposed method over the compared approaches.

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