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LEARNING ASYMMETRIC HASH CODE FOR REMOTE SENSING IMAGE RETREIVAL

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ABSTRACT:

An essential activity in remote sensing applications is remote sensing image retrieval (RSIR), which looks for a group of objects that are comparable to a particular query image. With regards to retrieval performance, deep hashing learning, the current widely used approach, has produced positive results. One method is the extraction of semantic features from remote sensing photos using a variety of deep neural networks. The high-dimensional deep characteristics are then mapped to the low-dimensional binary codes using hashing techniques, on the other hand. This kind of approach makes a symmetrical attempt to learn a single hash function for both the query and database samples. However, it takes a lot of time to build the hash codes for large-scale database images as the number of database samples grows. This method attempts to train a single hash function symmetrically for both the query and database samples. However, when the number of database samples increases, it takes a long time to create the hash codes for large-scale database images. Additionally, we match the semantic data from each image with the similarity data from pairs of photos as supervised data to train a deep hashing network, which enhances the representational strength of deep features and hash codes. The experimental findings on three open datasets show that the suggested method performs better than symmetric methods in terms of retrieval accuracy and effectiveness. The source code for the TGRS2022 Demo AHCL is accessible at https://github.com/weiweisong415/Demo AHCL.

KEYWORDS:

Remote sensing image retrieval (RSIR),content-based image retrieval (CBIR),bag of-visual words (BoVW), Fisher vector (FV),vector of locally aggregated descriptors (VLAD),convolutional neural networks (CNNs), deep hashing neural networks (DHNNs)

I.INTRODUCTION

Remote sensing photographs captured by satellites or other aerial vehicles have significantly improved in volume and resolution as a result of the quick development of Earth observation technologies. It is now urgently necessary to figure out how to manage and analyze these enormous quantities of remote sensing photos. The process of retrieving images

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from remote sensors (RSIR), which tries to find scenes or images that are comparable to a given query image, has received a lot of attention [1].

The majority of early RSIR research approaches used annotated metadata to find related photos, such as location, time of acquisition, and sensor type. This type of technique typically produces inaccurate retrieval results since the employed and notated tags cannot accurately describe image information. While using image characteristics to represent the visual content of remote sensing images, content-based image retrieval (CBIR) approaches achieve satisfactory performance. Feature extraction and a similarity measure are typically the two major components in a CBIR system. The retrieval framework used by RSIR is shown in Fig. 1.

The designed feature descriptors are used to represent both the query photos and the database images during the feature extraction process. Deep features and hand-crafted features can be separated from the retrieved features. Low-level and mid-level features are among the hand-crafted features. Low-level features including texture features [2], spectral features [3], and form features [4], [5] were frequently utilized in RSIR in previous decades. Additionally, a number of encoding methods, including the bag of visual words (BoVW) [6], Fisher vector (FV) [7], and vector of locally aggregated descriptors (VLAD) [8], were used to convert the low-level characteristics into midlevel features, which produced positive retrieval outcomes.

However, the "semantic gap"—a term used to describe the ability of hand-crafted features to effectively reflect the semantic information in remote sensing images—limits their ability to do so. convolutional neural networks (CNNs) have been widely used in remote sensing applications, such as land cover categorization [9]–[14], scene recognition [15]–[16], and picture fusion [17]–[20], as deep learning has advanced in the computer visual area. Researchers have successfully used high-level characteristics retrieved by CNNs for RSIR in recent years [21]–[23].

A similarity metric is then used to determine how similar the photos in the database and the query are after the remote sensing image features have been collected. Euclidean distance is the standard measure of similarity used by the majority of current techniques. The Euclidean distance between two real-valued features must be calculated, though, and this might take some time, particularly for deep features with high dimensions [24]. Hashing algorithms have been extensively explored for image retrieval in order to address the aforementioned difficulty [25], [26]. The primary concept behind hashing techniques is to learn a set of hash functions that translate high-dimensional picture attributes into low-dimensional hash codes (i.e., binary codes). The feature distance between two binary codes, also known as the Hamming distance, can be calculated with far less difficulty than the sophisticated Euclidean distance calculation thanks to the straightforward XOR operation.

Deep hashing techniques have recently taken over as the standard RSIR techniques. Deep neural networks are employed to extract semantic information for efficient content representation, on the one hand. On the other hand, learning binary codes for quick similarity computation is done using hashing algorithms. For RSIR, a number of deep hashing techniques have been developed over the last few years. For large-scale RSIR, Lietal. proposed deep hashing neural networks (DHNNs) [27]. In particular, compact hash codes and high-level semantic features were learned using pre-trained CNNs and hashing networks, respectively. To maintain the coding balance intuitively, Tang et al. integrated hash learning into the generative adversarial architecture [28]. Furthermore, a cohesion-intensive deep hashing model for RSIR was created, where the cohesiveness of image hash codes within a class was enhanced using a weighted loss technique [29]. In order to increase retrieval performance, Shan et al. coupled hard probability sampling with hash code learning in a deep network in [30]. An adversarial hash learning model and a deep feature learning model are the components of the feature and hash (FAH) learning approach for RSIR that was proposed in [31]. The simultaneous retrieval and classification of remote sensing images was proposed by Song et al. in [32] using a unique deep hashing network. The aforementioned approaches make an effort to symmetrically learn one hash function for both query and database sample data. The output of the network is binarized in order to obtain the hash codes for query and database pictures. The training of these symmetric deep hashing networks, however, often takes a long period as database samples grow larger.

Jiang et al.'s (Jiang et al.) [33] suggested an asymmetric deep supervised hashing (ADSH) approach to produce the hash codes of query and database images in an asymmetric way. In greater detail, while the hash codes of database images are directly learned by resolving the designed objective function, the hash codes of query images are retrieved via the feedback computation of the deep hashing network. We present asymmetric hash code learning (AHCL), a unique asymmetric hashing method for RSIR in this research, which is inspired by [33]. Unlike ADSH, which only took into account similarity information between image pairs, we carefully designed a better object function that trains a deep hashing network end-to-end while simultaneously combining the semantic information of each image and similarity information between image pairs. Our suggested technique may extract the more discriminative deep features to describe the complicated remote sensing images by merging various types of supervised information in object function.

II. LITERATURE SURVEY

Similarity search is a key challenge in information retrieval and data mining applications [34]. With the rapid expansion of image data, the search time for similar products is often expensive or unattainable. Approximate closest neighbor (ANN) search has become a prominent study issue in recent years. Among ANN approaches, hashing has been one of the most popular and useful strategies due to its encouraging efficiency in both speed and storage. In order to transfer the image points from the original space into a Hamming space, a set of hash functions must be learned. Each image is converted into a compact binary code by the hashing process, and the similarity in the original space is also maintained. Unsupervised hashing and supervised hashing are the two main categories of learning to hash techniques currently available. The hash functions for unsupervised hashing algorithms are learned from unlabeled training data. The most common unsupervised hashing techniques are density sensitive hashing (DSH) [37], iterative quantization (ITQ) [36], and spectral hashing (SH) [35]. Unsupervised hashing techniques are frequently susceptible to noise and image changes since hash codes have a limited capacity. supervised hashing approaches, on the other hand, aim to use supervised data to learn hash codes. Point-wise labels, pair-wise labels, and ranking labels are the three various ways that the supervised information can be presented. Both sparse embedding and least variance encoding (SELVE) and supervised hashing with kernels (KSH) are examples of typical supervised hashing techniques. Additionally,

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over the past few years, a number of deep hashing techniques have been created. Consider Xia et al. split the hash learning procedure into two stages: a stage of approximating binary codes, followed by a stage of simultaneously fine-tuning image features and hash functions via a CNN [40]. For simultaneous feature learning and hash code learning for image retrieval, Li et al. employed pair wise labels information [41]. Additionally, Zhang et al. [42] used pseudo labels to train a deep hashing network unsupervised for scalable picture retrieval. B. Using Deep Hashing in RSI.

III.PROBLEM STATEMENT

To represent the content of an image, traditional RSIR approaches use hand-crafted features. The hand-crafted features, however, fall short in their ability to adequately characterise the semantic information included in remote sensing photos, resulting in subpar retrieval outcomes. Combining CNNs with hashing methods has become the standard way of RSIR because to the significant advancements made by deep learning in the field of computer vision. Numerous related algorithms have been created in the recent years. For single-source RSIR [27] and cross-source RSIR [43], for instance, Li et al. presented deep hashing neural networks (DHNNs). A semi-supervised deep adversarial hashing (SDAH) was suggested in [28] for large-scale RSIR workloads. The class variable and hash code in such a work were produced using a residual auto-encoder (RAE). To then regularise the aforementioned vectors, two multi-layer networks were built. Shan et al. presented the hard probability sampling hash retrieval method in [30] in an effort to enhance retrieval performance.

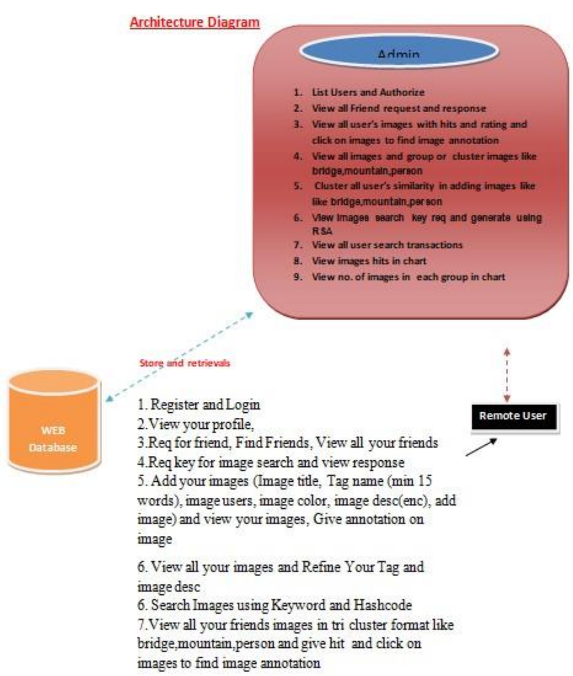
To extract dense features from images and map the dense features onto compact hash codes, respectively, Liu et al. chose a deep feature learning model and an adversarial hash learning model in [31]. To further achieve retrieval and classification of remote sensing images, Song et al. created a unified deep-hashing framework [32].

METHODOLOGY

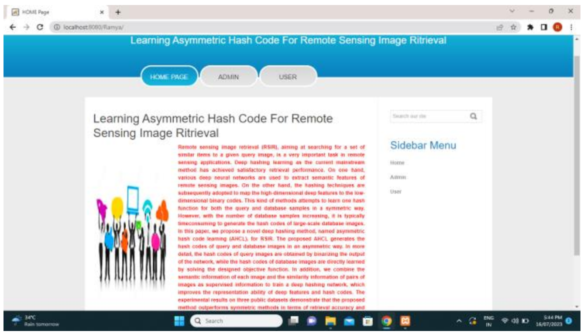
Since a deep hashing convolutional neural network (DHCNN) is built to simultaneously extract deep features and hash codes from distant sensing photos, image retrieval is quick.

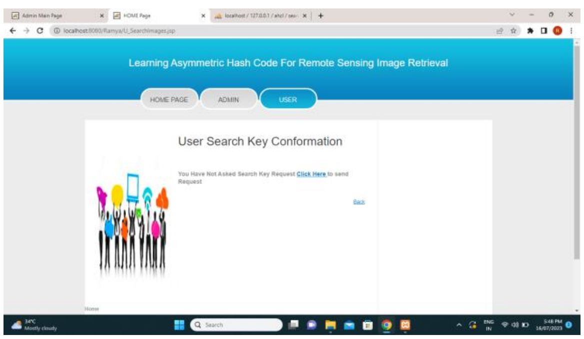
We provide a brand-new asymmetric deep hashing algorithm for RSIR in order to increase retrieval effectiveness. The proposed approach's schematic is presented by the system. The corresponding methods are thoroughly introduced in the section that follows.

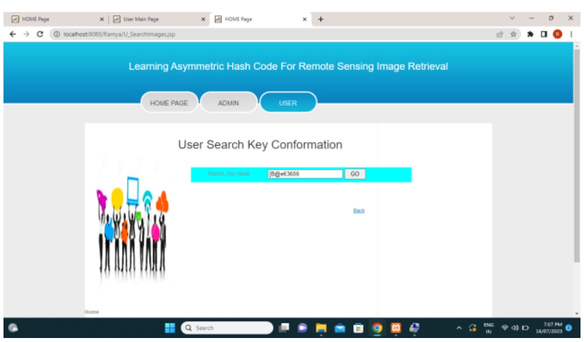
ARCHITECTURE:

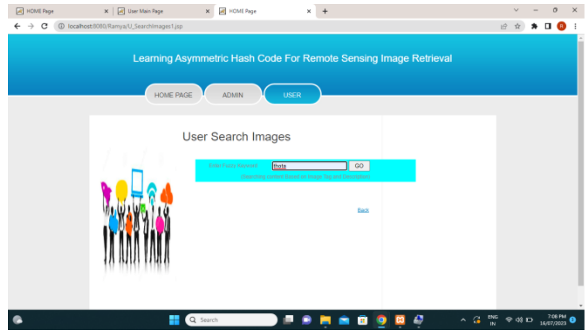


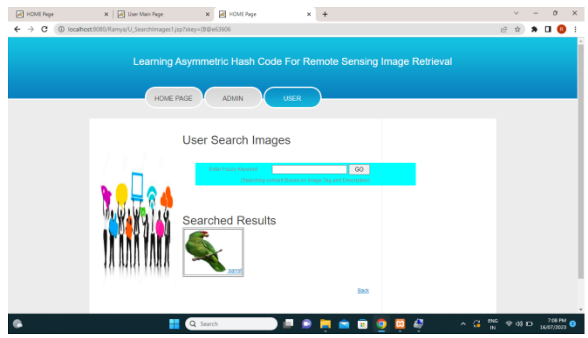
IV.RESULTS

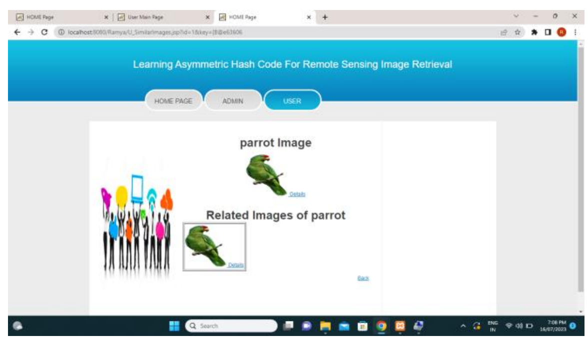












V.CONCLUSION

Deep hashing-based RSIR techniques currently make an effort to symmetrically learn one hash function for both query and database samples. Specifically, binarizing the network output yields the hash codes for all query and database remote sensing images. However, generating the hash codes for large database images often takes a while. In order to achieve this, we suggested a fresh asymmetric deep hashing technique for fast RSIR. More specifically, the hash codes of query images are acquired through the deep hashing network's feedback calculation, whereas the hash codes of database images are directly learned through the solution of the objective function. The suggested asymmetrical approach enhances the large-scale retrieval task's requirement for efficient hash code creation. . Additionally, to improve the ability of feature representation, the created loss function simultaneously utilises the semantic information and similarity information of images. Finally, the experimental findings support the proposed approach's superiority over the approaches that were compared.

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