International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7
DOI: https://doi.org/10.17762/ijritcc.v11i7.7831
***Article Received**: 16 April 2023 **Revised**: 19 June 2023 **Accepted**: 02 July 2023*

Impact of Feature Representation on Remote Sensing Image Retrieval

Monali P. Mahajan[1], Prof. Dr. S. M. Kamalapur[2]
[1]Research Scholar, Department of Computer Engineering,
K. K. Wagh Institute of Engineering Education and Research, Nashik,
Savitribai Phule Pune University, Pune, Maharashtra, India
mjmetkar@kkwagh.edu.in
[2]Professor and Research Guide, Department of Computer Engineering,
K. K. Wagh Institute of Engineering Education and Research, Nashik,
Savitribai Phule Pune University, Pune, Maharashtra, India
smkamalapur@kkwagh.edu.in

Abstract - Remote sensing images are acquired using special platforms, sensors and are classified as aerial, multispectral and hyperspectral images. Multispectral and hyperspectral images are represented using large spectral vectors as compared to normal Red, Green, Blue (RGB) images. Hence, remote sensing image retrieval process from large archives is a challenging task. Remote sensing image retrieval mainly consist of feature representation as first step and finding out similar images to a query image as second step. Feature representation plays important part in the performance of remote sensing image retrieval process. Research work focuses on impact of feature representation of remote sensing images on the performance of remote sensing image retrieval. This study shows that more discriminative features of remote sensing images are needed to improve performance of remote sensing image retrieval process.

Keywords - Aerial, multispectral, hyperspectral images, feature representation, retrieval.

I. INTRODUCTION

Remote sensing is the acquisition of information about an object without physical contact of that object. Remote sensing images are captured using different platforms and sensors. Characteristics of these images are specified by different types of resolutions as spatial, spectral, temporal, radiometric resolution. Based on platforms, sensors, acquisition, resolution these images are classified as aerial, multispectral and hyperspectral. Remote sensing images are having different applications and properties. As compared to normal color images these images are having high resolution and hence study of these images plays important role in many applications and challenges. Aerial images are captured using airborne platforms like aircraft, drones, balloons, satellites or Unmanned Aerial Vehicle (UAV). These images have wide applications in acquisition of land, engineering, geology, mining, military, archeology, geography, oil and gas surveying, surveillance, commercial advertising etc. Aerial images based on spectral bands or channels can be classified as classified as multispectral images. These images have more spectral information for every pixel rather than traditional color cameras. Multispectral images can be captured by ground based and airborne platforms. Multispectral images captured has narrow bands upto 100 depending on wavelengths. These bands of multispectral images consist of red, green, blue(RGB) channels as of RGB image with additional channels of infrared. These images are represented using three dimensional data cube as shown in Figure 1 as (x, y, λ) where (x, y) contains spatial information and λ records spectral information.

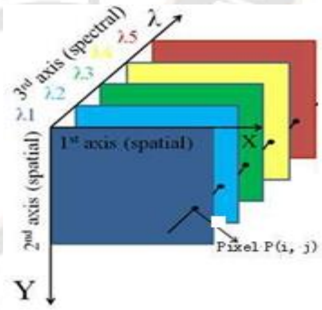

Figure 1: Data cube of multispectral image [1]

As shown in Figure 1, this multispectral data cube has 5 bands of different spectral channels. Here each pixel in an image will be represented at location p(i,j) as (x1,x2….xn) where x corresponds to spectral reflectance value for each band and n indicates number of bands. Multispectral imaging is used in variety of applications which includes military target tracking, space based imaging, weather forecasting, documents and art works, agriculture, healthcare, etc. Compared with multispectral images hyperspectral images captured using special platforms, sensors have more continuous bands. These images are captured using special sensors and satellites like AVIRIS, NASA EO-1 satellite, Hyperion Sensors, ROSIS,

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7
DOI: https://doi.org/10.17762/ijritcc.v11i7.7831
***Article Received**: 16 April 2023 **Revised**: 19 June 2023 **Accepted**: 02 July 2023*

MODIS etc. Hyperspectral images are represented using a type of data cube, known as image cube. Images collected using hyper spectral sensors are having hundreds of bands which stores spectral and spatial information in a data cube as shown in Figure 2. This data cube can be as (x, y, λ) where (x, y) contains spatial information and λ records spectral information.

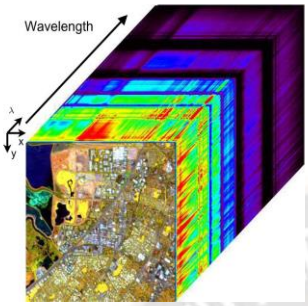

Figure 2: 3-D Hyperspectral cube [2]

Differentiating between different materials with greater details is possible in hyperspectral images due to high volume of spectral bands. These detailing of application can be improved by considering spatial features of image like shape, texture, geometrical structure. Hyperspectral images have a wide range of applications in remote sensing, agriculture, astronomy, chemical imaging, medical, surveillance and many more. So, as observed from this study remote sensing images of types aerial, multispectral and hyperspectral are having rich information as compared to normal RGB images and they are used in variety of applications. Among these images multispectral and hyperspectral images have more spectral information. Due to spectral information of these images more detailing of the application can be studied. Depending upon application these images are captured repeatedly and are stored in large archives. Finding similar images to a query image from these large archives is one of the challenging tasks in image processing. Remote sensing image retrieval (RSIR) refers to searching and returning images of interest from a large database for a given query image. General RSIR system is shown in Figure 3.

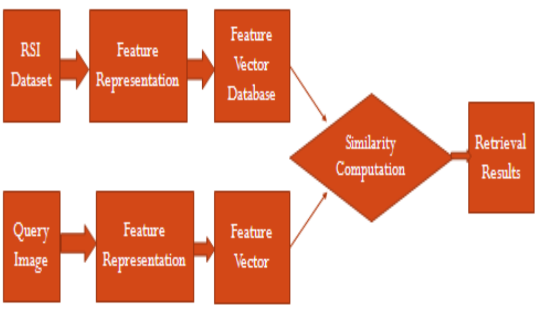

Figure 3: Remote sensing image retrieval process

As shown in Figure 3 retrieval process of remote sensing images consists of dataset of images where all images are stored. These images will be captured using special platforms and sensors. Next step in retrieval process is feature representation of these images. Features of these images will be represented using different methods. These features are then used for similarity comparison. After forming features of database images, next step in retrieval process is to process query image. Here query image will be taken and features of this query image will be represented. Comparison of this query image features with features of database images will be done afterwards. This similarity comparison can be performed using different methods. After finding similarity matched images will be retrieved from the database. In recent years various methods for retrieval of aerial, multispectral, hyperspectral images was proposed by researchers. Further sections focuses on literature survey of feature representation techniques used for retrieval of aerial, multispectral, hyperspectral images.

Section II focuses on feature representation techniques used for retrieval of aerial images. Feature representation techniques used for multispectral image retrieval is focused in section III followed by hyperspectral image retrieval in section IV. Section V focuses on performance analysis.

II. AERIAL IMAGE RETRIEVAL

As shown in Figure 3 RSIR process mainly consist of two steps as feature representation and similarity comparison. Features of aerial images are represented using various techniques. The feature representations can be divided into different categories including the feature representation using hashing, low level, middle level and high level feature representations. Following section focuses on feature representation techniques used for aerial image retrieval.

A. Feature representation using hashing

Images are represented using hash codes in different ways. Hashing is combined with other techniques for improving the performance.

Method for creating hash functions was presented by Peng Li et. al.[3]. Part of model parameter values are randomly generated and the remaining ones are trained based on remote sensing images. Hash functions are effective due to randomness and trained model parameters. Multicode hashing by Reato et. al.[4] presented unsupervised method that represents each image with primitive-cluster sensitive multi-hash codes. Initially images are characterized using descriptors and multi hash codes and then retrieval is performed using multi hash code matching scheme. Low rank hypergraph hashing(LHH) was presented by Kong et. al.[5]. Initially l2-1 norm is used to reduce the noise and redundancy in features. With this low rankness is also imposed on this matrix to make use of its global structure. Then hypergraph is used to capture

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7
DOI: https://doi.org/10.17762/ijritcc.v11i7.7831
Article Received: 16 April 2023 Revised: 19 June 2023 Accepted: 02 July 2023

the high order relationship among the data which is suitable to represent remote sensing images having complex structure. Han et. al.[6] developed a cohesion intensive deep hashing model which uses residual net. This residual net aims to avoid gradient vanishing and explosion when it reaches to a certain depth. Roy et. al.[7] used deep metric and hash code for retrieval of aerial images. Pre trained model Inception Net is used to extract image representation, this image representation is fed to metric and hash code leaning network. Fernandez et. al.[8] introduced a novel unsupervised hashing method a new probabilistic latent semantic hashing (pLSH). Three main steps are to learn the hash codes. In the first step, several groups of remote sensing archive is done. In second step, topic computation is done where the pLSH model is used to uncover highly descriptive hidden patterns from each group. In the last step of hash code generation data probability distributions are thresholded to generate final binary codes. A quantized deep learning was proposed by Li. Et. al.[9]. The weights and the activation functions are binarized to low bit representations for less storage space and computing resources. Experimentation was done on these methods using various datasets. Summary of different hashing techniques with various datasets used is summarized in Table I.

TABLE I. AERIAL IMAGE RETRIEVAL METHODS USING HASHING AND RESPECTIVE DATASETS

Method	Dataset description
Partial Randomness Hashing [3]	SAT4, SAT6, Normalized to 28x28
An Unsupervised Multicode Hashing Method [4]	UCMerced having Image size 256x256 with 21 classes and 10,000 total images
Low-Rank Hypergraph Hashing [5]	UCMerced having image size 256x256 with 21 classes and 10,000 total images, SAT4 with image size normalized to 28x28 ,SAT6 with image size normalized to 28x28 and CIFAR10 with image size normalized to 32x32
Cohesion Intensive Deep Hashing [6], Metric-Learning based Deep Hashing Network [7]	UCMerced having image size 256x256 with 21 classes and 10,000 total images and AID having 10,000 images with image size 600x600 with 30 classes
pLSH[8]	UCMerced having image size 256x256 with 21 classes and 10,000 total images , EUROSAT having image size of 64x64

Low level, middle level and high level are other feature representation techniques used to represent features of aerial images.

B. Feature representation using low level features - Texture

Aerial images are represented using various low level features. Texture feature of the aerial images can be used to represent the images. Various ways to describe texture features of the images are discussed in this section.

Gabor texture was proposed by Hongyu et. al.[10]. Initially Gabor features of images are obtained by applying different scales and orientations. K means is used to perform unsupervised classification of the obtained Gabor features. Color moment and gray level co-occurrence matrix (GLCM) was proposed by Maheshwary et. al.[11] in which color features are combined with GLCM. Color Gabor wavelet texture (CGWT) and color Gabor opponent texture (CGOT) are the two texture descriptors presented by Shao et. al.[12]. Unichrome and opponent features are computed initially across different color channels at different scales. Gabor and opponent features are considered afterwards. Due to these two representations remote sensing images having multiple objects are represented in better way. Global morphological texture descriptors was proposed by Aptoula[13]. Circular covariance histogram and rotation invariant points triplets was explored. Bouteldja et. al.[14] proposed retrieval on the basis of steerable pyramids using RGB and CIElab color systems. Statistical measures are used to extract the texture features. Advanced local binary patterns (LBP) by Tekeste et. al.[15] presented comparative study in order to analyze and compare advanced LBP variants in remote sensing content based image retrieval domain. Multi scale patch-based local ternary pattern (LTP) and vector encoding based technique was proposed by Sukhia et. al.[16]. The technique down samples an image in three scales, each down sampled image utilizes LTP to obtain upper and lower texture images, and divides them into dense patches to build a final histogram representation.

C. Feature representation using low level features – Shape

Shape is another low level feature that is used to represent an image. This section focuses on shape features used to represent aerial images. Lowe et. al.[17] presented a method for extracting distinctive invariant features. These features are also used for object recognition. Matching of individual features is done using fast nearest neighbor algorithm, then followed by Hough transform for identification of clusters. Retrieval based on local shape association presented by Ma et. al.[18]. Initially region extraction is performed, followed by polygonal approximation to the region shape, and local features of the polygons are hashed to provide an association space. This space becomes the indexing structure through which retrieval takes place. Scott et. al.[19] developed a novel indexing structure in which automatic extraction of objects of satellite imagery of multiple scales is done and then these objects are encoded into bitmap shape representation. Wang et. al.[20] presented a novel feature design to precisely describe Visual Salient Point(VSP) in images. Visual attention model is used to separate the salient regions from the background in the images. The similarity between images is measured using the VSP features. Table II summarizes methods used for aerial image

retrieval using low level representation and its datasets.

TABLE II. AERIAL IMAGE RETRIEVAL METHODS USING LOW LEVEL FEATURES AND RESPECTIVE DATASETS

Method	Dataset description
Improved color texture descriptors [12], Global Morphological Texture Descriptors [13], Multiscale Texture Features [14], Advanced Local Binary Patterns [15], Visual salient point features [20]	UCMerced having image size 256x256 with 21 classes and 10,000 total images
Multi-scale local ternary pattern [16]	UCMerced having image size 256x256 with 21 classes and 10,000 total images , Satellite optical land cover dataset with image size 256x256

In many applications, single type of low level features lacks enough discrimination. Therefore, researchers combine diverse types of features to improve the retrieval results.

D. Feature representation using middle level features

Middle level features are obtained initially by obtaining hand crafted descriptors and then aggregating these into different encoding methods. Pattern spectrum and multiscale shape representation was introduced by Maragos et. al.[21]. A discrete-size family of patterns was used. Based on pattern spectrum entropy like shape size complexity measure is developed. For representations of shape, reduced morphological skeleton transform is introduced for discrete binary and graytone images. Jegou et. al. [22] proposed aggregating local image descriptors into a vector. Jointly optimizing the dimension reduction and the indexing algorithm is presented. Local invariant features were by investigated by Yang et. al.[23]. Aerial and satellite images having high resolution are represented in a better way using local features which allows to recognize objects in great range. Sparse feature representations were learned by Zhou et. al.[24] using an unsupervised feature learning framework based on auto encoder. Low level feature descriptors are extracted and exploited and then are used for encoding low level feature descriptors. Yang et. al. [25] proposed a method to improve recognition performance of a typical Bag of Words (BoW) framework by representing images with local features extracted from base images. Bosilj et. al. [26] presented a novel morphological descriptors called pattern spectra for retrieval. These spectra histogram like structure used to describe global distributions image components. Main contribution of this lies in their dense calculation, at a local scale, thus enabling their combination with sophisticated visual vocabulary strategies. Vector of Locally Aggregated Descriptors (VLAD) was presented by Imbriaco et. al. [27]. Study of various system parameters like multiplicative and additive attention mechanisms and descriptors dimensionality was done. Table III shows summary of aerial image retrieval using middle level features and dataset used for experimentation.

TABLE III. AERIAL IMAGE RETRIEVAL USING MIDDLE LEVEL FEATURES AND RESPECTIVE DATASETS

Method	Dataset description
Using Local Invariant Features [23]	UCMerced having image size 256x256 with 21 classes and 10,000 total images
An improved Bag-of-Words framework for [25]	Landsat-5 TM with image size of 512x512

E. Feature representation using high level features

Recently, due to hierarchical structure of convolutional neural network (CNN) it is possible to simulate very complex non liner functions. It is also useful in automatically learning parameters for training and testing. It is possible to capture essential characteristics and high level features of aerial images using CNN models. Four unsupervised CNNs was designed by Li et. al. [28] to generate four types of unsupervised features from the fine level to the coarse level. Four traditional feature descriptors, including LBP, GLCM, maximal response 8 (MR8), and scale-invariant feature transform (SIFT) was also implemented. Xiong et. al.[29] introduced new attention module to CNNs structure and in multi task learning network structure is proposed. A new method for constructing more challenging datasets is proposed to better validate proposed schemes. Chaudhuri et. al.[30] proposed a novel Siamese graph convolution network (SGCN). Region adjacency graph (RAG) image representation in terms of localized regions is studied. This method captures important scene information which then can be further used for image to image correspondence. In standard GCN features there is lack of discriminative features for fine grained classes and hence SGCN was proposed for evaluating the similarity between pair of graphs. So given RAG representation the target is to learn semantically closer images while excluding dissimilar images apart. Cao et. al.[31] presented a retrieval method based on triplet deep metric learning CNN. Triplet network with metric learning objective function is used to obtain representative features of the image.

Chung et. al. [32] proposed a method by merging group convolution with attention mechanism and metric learning, resulting in robustness to rotational variations. Two step training strategy was proposed in which in first step the high-level features are obtained and in second step fine-tuning the network with metric learning approach to learn the discriminative features. Liu. et. al. [33] proposed a novel method center metric learning and combined it with a new type of loss as positive negative center loss due to which within class variations are successfully coped up. Combination of center-metric learning, similarity distribution learning and aerial scene classification is combined into one CNN for better generalization ability. Yun et. al. [34] proposed a method using coarse-to-fine strategy with deep network image retrieval. Detailed information in complex remote sensing images is learned using triplet loss function to improve the retrieval performance. Cao et.al. [35] developed a deep metric learning approach with Generative Adversarial Network(GAN) regularization for retrieval of high spatial resolution remote sensing images. Initially a high level feature is extracted which includes convolutional layers and fully connected layers, where each of fully connected layer is constructed by Deep Metric Learning(DML) for maximizing the interclass variation and minimize interclass variations. For validating the qualities of extracted high level features and to ease the over fitting problems the GAN is adopted. Liu et. al. [36] proposed a method to learn deep features of image for accurate image similarities for retrieval with latent relationship embedding. AlexNet was used to extract high level semantic features and for image similarities latent relationship is considered. Li et. al.[37] proposed an adaptive multi-proxy framework and proxy-based deep metric learning method. First, an intra cluster sample synthesis strategy with a random factor is proposed, which uses the limited samples in batch to synthesize more samples to enhance the network's learning of unobvious features in the class. To assign multiple proxies according to the cluster of samples within a class proxy assignment method is proposed. To accurately and comprehensively measure the sample class similarity, weights for each proxy is determined according to the cluster scale. Table IV shows summary of aerial image retrieval using high level features and datasets used for experimentation.

TABLE IV. AERIAL IMAGE RETRIEVAL USING HIGH LEVEL FEATURES AND RESPECTIVE DATASETS

Method	Dataset description
Aggregated Deep Local Features [27]	UCMerced having image size 256x256 with 21 classes and 10,000 total images, Satellite Remote with image size of 56x256, SIRI-WHU having image size of 200x200, NWPU-RESISC45 having image size of 256x256 with 45 classes and 31,500 total images
Unsupervised Feature Learning and Collaborative Affinity Metric Fusion[28]	UCMerced having image size 256x256 with 21 classes and 10,000 total images, Wuhan University (WH) dataset with image size of 600x600 having 19 classes and 1005 total images
A Discriminative Feature Learning Approach [29]	AID having image size 600x600 with 30 classes and 10,000 total images, Pattern Net having image size of 256x256 with 38 classes and 30400 total images
SGCN[30], Triplet Deep Metric Learning Network [31], Eagle-Eyed Multitask CNNs [33]	UCMerced having image size 256x256 with 21 classes and 10,000 total images, Pertinent having image size of 256x256 with 38 classes and 30400 total images
Coarse-to-Fine Deep Metric Learning[34]	Google Earth South Korea Dataset with image size of 1080x1080
Deep Metric Learning With GAN Regularization [35]	UCMerced having image size 256x256 with 21 classes and 10,000 total images, NWPU-RESISC45 having image size of 256x256 with 45 classes and 31,500 total images
Deep Feature Learning With Latent Relationship Embedding [36]	UCMerced having image size 256x256 with 21 classes and 10,000 total images ,WHU-RS19 Wuhan University (WH) dataset with image size of 600x600 having 19 classes and 1005 total images and RSSCN7 having image size of 400x400 having 7 classes and 2800 total images
Adaptive Multi-Proxy [37]	UCMerced having image size 256x256 with 21 classes and 10,000 total images, RSSCN7 having image size of 400x400 having 7 classes and 2800 total images, AID having image size 600x600 with 30 classes and 10,000 total images , Pertinent having image size of 256x256 with 38 classes and 30400 total images

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7
DOI: https://doi.org/10.17762/ijritcc.v11i7.7831
***Article Received**: 16 April 2023 **Revised**: 19 June 2023 **Accepted**: 02 July 2023*

Features of aerial images are represented using various types of techniques including hashing, low, middle and high level representations. Similarity measures used for aerial image retrieval includes Euclidean Distance, Manhattan Distance, Chi Square Distance Calculation, Cosine distance, Hamming distance, Minkowski norms, Hash lookup, Mahalanobis Distance. From this study it has been observed that more discriminative features of aerial images can be obtained in future for improving performance of aerial image retrieval process.

III. MULTISPECTRAL IMAGE RETRIEVAL

Multispectral images have more spectral information rather than traditional color cameras and are captured by ground based and airborne platforms. Multispectral images captured have narrow bands up to 100 depending on wavelengths. These bands of multispectral images consist of red, green, blue channels as of RGB image with additional channels of infrared. Due to spectral information, retrieving similar images from dataset of multispectral images is a challenging task. Researchers used various techniques for feature representation and similarity measure of multispectral images. This section focuses on multispectral image retrieval methods.

To represent and retrieve image regions similar to a query region using texture features have long been used in remote sensing applications. Fourier power spectrum, spatial co-occurrence, wavelets, Gabor filters, etc. are the various representations of texture that have been proposed. Several different texture representations for retrieval using multispectral satellite images were investigated by Newsam et. al [38]. Framework based on a query-by-example with a manually chosen ground truth dataset, allows different combinations of texture representations and spectral bands to be compared. It has been observed that use of all spectral bands improves the retrieval performance, and co-occurrence, wavelet and Gabor texture features perform comparably. In the experiment by Joshi et. al. [39] high level feature extraction techniques that are scale invariant feature transform and Gabor descriptors are used. The novel approach is proposed in which both the feature descriptors are fused to retrieve the results. Wijitdechakul et. al. [40] studied semantic computing to measure the similarity between multispectral image and the meaningful keywords which according to the user's contexts is proposed in this method. This method acquire spectral features form the multispectral images and hence can be used for retrieval of multispectral images. A feature descriptor which combines the color coherent pixel information and GLCM texture features in multi scale domain was proposed by Sudheer et. al.[41]. The image is decomposed into coarse and detail coefficients using curvelet transform. To improve the directional information Gabor magnitude is computed for each coefficient. GLCM texture features are then extracted from the Gabor magnitude response. By combining the Color Coherence Vector (CCV) and GLCM using a curvelet and Gabor filter the novel feature set are developed. Chen et. al. [42] proposed a novel method for unsupervised multispectral remote sensing image retrieval based on hashing and GAN. The proposed method makes use of the unsupervised representation learning ability of GAN. To make the final output informative and representative, a new reconstruction loss exploits the latent codes in GAN. To further guide the training transfer learning and color histograms are used to generate an estimated similarity matrix. The output codes are made binary and compact using hash constraints. For testing stage, the hash codes of multispectral images can be computed in an end-to-end manner. Sathiyaprasad et. al. [43] proposed architecture of neural networks in feature extraction of images collected from satellites using fast recurrent convolutional neural networks (FRCNN). To identify objects and accurately locate them FRCNN is designed for retrieving the image collected by satellite without any loss of data. Table V shows summary of multispectral image retrieval methods with datasets used for experimentation.

TABLE V. MULTISPECTRAL IMAGE RETRIEVAL METHODS WITH RESPECTIVE DATASETS

Method	Dataset description
Retrieval Using Texture Features [38]	Five images from two geographic regions, California and Nebraska of 384x384 pixels, 4 spectral bands
Empirical Analysis of SIFT, Gabor and Fused Feature Classification Using SVM [39]	Multispectral Landsat 8 satellite Image 105 images of Landsat 8 sensors data of 30 meter resolution
Spectral Feature and Semantic Computing [40]	80 multispectral-images which are captured from UAV multispectral Sensor.
Multiscale Texture Analysis and Color Coherence Vector Based Feature Descriptor [41]	UCMerced having image size 256x256 with 21 classes and 10,000 total images
An End-To-End Adversarial Hashing Method [42]	EuroSAT having 10 land-use classes and have 13 bands with three different spatial resolutions of 10m, 20m and 60m per pixel. Each class contains 2000-3000 images. In total, the dataset has 27000 images.
FRCNN [43]	Dual-Source Remote Sensing Image Dataset(DSRSID) of 80 000 dual samples

Similarity measures used for multispectral image retrieval includes Euclidean Distance, Manhattan Distance, Chi Square Distance Calculation, Cosine distance, Hamming distance,

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7
DOI: https://doi.org/10.17762/ijritcc.v11i7.7831
***Article Received**: 16 April 2023 **Revised**: 19 June 2023 **Accepted**: 02 July 2023*

Minkowski norms, Hash lookup, Mahalanobis Distance. Multispectral images have more spectral bands as compared to aerial images, hence getting more discriminative features of these images for improving performance of the retrieval is a challenging task.

IV. HYPERSPECTRAL IMAGE RETRIEVAL

Compared with multispectral images hyperspectral images captured using special platforms, sensors have more continuous bands. Images collected using hyper spectral sensors are having hundreds of bands which stores spectral and spatial information in a data cube. Due to rich spectral information retrieving similar images from dataset of hyperspectral images is a challenging task. Various techniques for feature representation and similarity measures were used for hyperspectral image retrieval.

Hyperspectral image retrieval considering rich spectral information based on endmember distance is proposed by Gran˜a et. al. [44]. Endmember induction algorithms (EIAs) are used to obtain features of hyperspectral images. Dictionaries for the mining of hyperspectral databases is proposed by Veganzones et. al.[45]. Various distance like Normalized Dictionary Distance(NDD) and the Fast Dictionary Distance(FDD) are used to compare the results against Normalized Compression Distance(NCD) over the different datasets of hyperspectral images. A novel system with unsupervised unmixing and consideration of spectral and spatial features of hyperspectral images was proposed by Veganzones et. al. [46]. EIA is used to obtain spectral features and spatial features are computed as abundance image statistics. Bag of endmember for hyperspectral image descriptors is proposed by Ömrüuzun et. al. [47]. Two modules were proposed where the first module two types of descriptors are used for representing hyperspectral image and hierarchical strategy to evaluate descriptors similarity for retrieving hyperspectral images. Deep Convolutional network with Generative Adversarial Networks (GAN) for deep feature extraction of spatial and spectral features by Chen. et. al [48]. One bit transform is used for reducing bands of hyperspectral image. Spectral vector is obtained using manual selection of pure pixel and spatial vector using neighbor pixels of pure pixels from principal bands. These two vectors are combined using vector stacking (VS) approach. Dimensionality reduction using t-distributed Stochastic Neighbor Embedding-based Nonlinear Manifold (t-SNE-based NM) hashing and Deep Convolutional network with Generative Adversarial Networks(GAN) for deep feature extraction of spatial and spectral feature is proposed by Zhang et. al [49] Spectral sensitivity functions for hyperspectral image retrieval is introduced by Ahmed et. al. [50]. These functions are used to extract hyperspectral image features in a better way. With this a new dataset is designed by authors for hyperspectral remote sensing retrieval and classification. Table VI shows summary of hyperspectral image retrieval methods with dataset used for experimentation.

TABLE VI. HYPERSPECTRAL IMAGE RETRIEVAL METHODS WITH RESPECTIVE DATASETS

Method	Dataset description
An endmember-based distance [44]	synthetic data
Dictionary based [45]	HyMAP data cube 2878 lines,512 samples and 125 bands.
A Spectral/Spatial CBIR System [46]	Synthetic Dataset, HyMAP data cube 2878 lines,512 samples and 125 bands.
Using Bag Of Endmembers Image Descriptors [47]	EO-1 Hyperion sensor, 3461x256 pixels with a spatial resolution of 30m, 119 spectral bands
Deep Spectral-Spatial Feature Extraction Based on DCGAN[48]	AVIRIS data, 224 spectral bands between 0.4 and 2.5 micrometers, and the spatial resolution is 20 m, the spectral resolution is 10 nm.
Deep Spectral-Spatial Feature Extraction with DCGAN and Dimensionality Reduction Using t-SNE-Based NM Hashing [49]	NASA data, which contains 224 spectral bands between 0.4 and 2.5 um. The spatial resolution is 20 m, and the spectral resolution is 10 nm.
A Preliminary Study Based on Spectral Sensitivity Functions [50]	ICONES Hyperspectral Satellite Imaging Dataset (ICONES-HSI) 224 contiguous spectral bands between 365 and 2497 nanometers, hyperspectral ANKARA archives

Similarity measures used for hyperspectral image retrieval are common with multispectral imaging with addition of multi index hashing. It can be noted from above study due to tremendous spectral information in hyperspectral images, processing these images is a challenging task. So retrieval of hyperspectral images considering spectral information with less computational time can be addressed in future.

V. PERFORMANCE ANALYSIS

Performance of the remote sensing image retrieval process is measured mainly using Recall, Precision Mean Average Precision (MAP) and Average normalized modified retrieval rank (ANMRR).

$$\text{Precision} = \frac{\text{Number of relevant retrieved images}}{\text{Total number of retrieved images}}$$

$$\text{Recall} = \frac{\text{Number of relevant retrieved images}}{\text{Total number of images}}$$

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7
DOI: https://doi.org/10.17762/ijritcc.v11i7.7831
***Article Received**: 16 April 2023 **Revised**: 19 June 2023 **Accepted**: 02 July 2023*

For each query sample i ∈ nq, ni retrieval results are returned, and this metric calculates the precision for each retrieval result j and then calculates the MAP value.

$$\mathrm{MAP} = \frac{1}{n_q}\sum_{i=1}^{n_q}\frac{1}{n_i}\sum_{j=1}^{n_i}\mathrm{precision(j)}$$

ANMRR is a measure that exploits the rank information among the retrieved images

$$\mathrm{ANMMR} = \frac{1}{Q_{tot}}\sum_{q=1}^{Q_{tot}}\mathrm{NMRR(q)}$$

Where, Q_{tot} is the total number of queries in the test and NMRR is normalized modified retrieval rank. Using these performance parameters Table VII summarizes results of retrieval methods for aerial images using various feature representation techniques. Table VIII summarizes results of retrieval methods for multispectral images. Table IX summarizes results of retrieval methods for hyperspectral images. This performance analysis shows remote sensing images needs to be represented using more comprehensive features to improve the performance of the retrieval process.

VI. CONCLUSION

Remote sensing image retrieval process refers to retrieving similar remote sensing images for a given query image from large archives. Feature representation of remote sensing images has impact on performance of remote sensing image retrieval process. Features of these images can be obtained using hashing, low level, middle level, high level representations. Performance of remote sensing image retrieval is comparatively better in case of high level representation. It is observed that more work is done on aerial images as compared to multispectral and hyperspectral images. Performance analysis shows that maximum precision for multispectral image retrieval is 82.02 and for hyperspectral image retrieval is 86.49 which can be improved further. Computational time to process large feature vectors of multispectral and hyperspectral images is one of the challenge that can be addressed in future.

REFERENCES

[1] Moataz Aboras, Hani Amasha, Issa Ibraheem(2015), Early detection of melanoma using multispectral imaging and artificial intelligence techniques American Journal of Biomedical and Life Sciences 2015; 3(2-3): 29-33

[2] Emmanuel Christophe, Corinne Mailhes, and Pierre Duhamel, Hyperspectral Image Compression: Adapting SPIHT and EZW to Anisotropic 3-D Wavelet Coding, IEEE Transactions On Image Processing, VOL. 17, NO. 12, DECEMBER 2008 1057-7149/$25.00 © 2008 IEEE

[3] P. Li, P. Ren, Partial randomness hashing for large-scale remote sensing image retrieval, IEEE Geosci. Remote Sens Lett 14 (3) (2017) 464–468.

[4] T. Reato, B. Demir, L. Bruzzone, An unsupervised multicode hashing method for accurate and scalable remote sensing image retrieval, IEEE Geosci. Remote Sens. Lett. 16 (2) (2019) 276–280.

[5] J. Kong, Q. Sun, M. Mukherjee, J. Lloret, Low-rank hypergraph hashing for largescale remote sensing image retrieval, Remote Sens (Basel) 12 (2020) 1164.

[6] L. Han, P. Li, X. Bai, C. Grecos, X. Zhang, P. Ren, Cohesion intensive deep hashing for remote sensing image retrieval, Remote Sens (Basel) 12 (1) (2020) 101.

[7] S. Roy, E. Sangineto, B. Demir, N. Sebe, Metric-learning-based deep hashing network for content-based retrieval of remote sensing images, IEEE Geosci. Remote Sens Lett. (2020) in press.

[8] R. Fernandez-Beltran, B. Demir, F. Pla, A. Plaza, Unsupervised remote sensing image retrieval using probabilistic latent semantic hashing, IEEE Geosci. Remote Sens Lett. (2020) in press.

[9] P. Li, L. Han, X. Tao, X. Zhang, C. Grecos, A. Plaza, P. Ren, Hashing nets for hashing: a quantized deep learning to hash framework for remote sensing image retrieval, IEEE Transactions on Geoscience and Remote Sensing (2020)

[10] Y. Hongyu, L. Bicheng, C. Wen, Remote sensing imagery retrieval based-on gabor texture feature classification, in: Proceedings of ICSP, 2004.

[11] P. Maheshwary, N. Srivastava, Prototype system for retrieval of remote sensing images based on color moment and gray level co-occurrence matrix, Int. J Comput Sci Issues 3 (2009) 20–23.

[12] Z. Shao, W. Zhou, L. Zhang, J. Hou, Improved color texture descriptors for remote sensing image retrieval, J Appl Remote Sens 8 (1) (2014), 083584.

[13] E. Aptoula, Remote sensing image retrieval with global morphological texture descriptors, IEEE Trans Geosci Remote Sens. 52 (2014) 3023–3034.

[14] S. Bouteldja, A. Kourgli, Multiscale texture features for the retrieval of high resolution satellite images, in: Proceedings of IWSSIP, 2015.

[15] I. Tekeste, B. Demir, Advanced Local Binary Patterns for Remote Sensing Image Retrieval, in: Proceedings of IGARSS, 2018.

[16] K. Sukhia, M. Riaz, A. Ghafoor, S. Ali, Content-based remote sensing image retrieval using multi-scale local ternary pattern, Digit Signal Process 104 (2020), 102765.

[17] D.G. Lowe, Distinctive image features from scale-invariant keypoints, Int J Comput Vis 60 (2) (2004) 91–110.

[18] A. Ma, I. Sethi, Local shape association based retrieval of infrared satellite images, in: Proceedings of ISM, 2005.

[19] G. Scott, M. Klaric, C. Davis, C. Shyu, Entropy-balanced bitmap tree for shapebased object retrieval from large-scale satellite imagery databases, IEEE Trans Geosci Remote Sens 49 (2011) 1603–1616.

[20] X. Wang, Z. Shao, X. Zhou, J. Liu, A novel remote sensing image retrieval method based on visual salient point features, Sensor Review 34 (4) (2014) 349–359.

[21] P. Maragos, Pattern spectrum and multiscale shape representation, IEEE Trans. Pattern Anal. Mach. Intell. 11 (7) (1989) 701–716

[22] H. Jegou, M. Douze, C. Schmid, P. Perez, Aggregating local descriptors into a compact image representation, in: Proceedings of CVPR, 2010.

[23] Y. Yang, S. Newsam, Geographic image retrieval using local invariant features, IEEE Trans Geosci. Remote Sens 51 (2) (2012) 818–832

[24] W. Zhou, Z. Shao, C. Diao, Q. Cheng, High-resolution remote-sensing imagery retrieval using sparse features by auto-encoder, Remote Sens Lett. 6 (2015) 775–783.

[25] J. Yang, J. Liu, Q. Dai, An improved bag-of-words framework for remote sensing image retrieval in large-scale image databases, Int J Digit Earth 8 (4) (2015) 273–292

[26] P. Bosilj, E. Aptoula, S. Lefevre, E. Kijak, Retrieval of remote sensing images with pattern spectra descriptors, ISPRS Int J Geoinf 5 (12) (2016) 228.

[27] R. Imbriaco, C. Sebastian, E. Bondarev, P. deWith, Aggregated deep local features for remote sensing image retrieval, Remote Sens (Basel) 11 (5) (2019) 493.

[28] Yansheng Li , Yongjun Zhang, Chao Tao and Hu Zhu ,Content-Based High-Resolution Remote Sensing Image Retrieval via Unsupervised Feature Learning and Collaborative Affinity Metric Fusion, Remote Sens., 8, 709; doi:10.3390/rs8090709(2016)

[29] W. Xiong, Y. Lv, Y. Cui, X. Zhang, X. Gu, A discriminative feature learning approach for remote sensing image retrieval, Remote Sens (Basel) 11 (3) (2019) 281.

[30] U. Chaudhuri, B. Banerjee, A. Bhattacharya, Siamese graph convolutional network for content based remote sensing image retrieval, Computer Vis. Image Underst 184 (2019) 22–30.

[31] R. Cao, Q. Zhang, J. Zhu, Q. Li, Q. Li, B. Liu, G. Qiu, Enhancing remote sensing image retrieval using a triplet deep metric learning network, Int J Remote Sens (2019).

[32] Chung, Woo-Jeoung Nam and Seong-Whan Lee , Rotation Invariant Aerial Image Retrieval with Group Convolutional Metric Learning Hyunseung 978-1-7281-8808-9/20/$31.00 ©2020 IEEE

[33] Y. Liu, Z. Han, C. Chen, L. Ding, Y. Liu, Eagle-eyed multitask CNNs for aerial image retrieval and scene classification, IEEE Trans Geosci Remote Sens (2020).

[34] Min-Sub Yun, Woo-Jeoung Nam, and Seong-Whan Lee, Coarse-to-Fine Deep Metric Learning for Remote Sensing Image Retrieval, Remote Sens. , 12, 219; doi:10.3390/rs12020219(2020)

[35] Yun Cao, Yuebin Wang , Junhuan Peng, Liqiang Zhang , Linlin Xu, Kai Yan , and Lihua Li, DML-GANR: Deep Metric Learning With Generative Adversarial Network Regularization for High Spatial Resolution Remote Sensing Image Retrieval, IEEE Transactions on geoscience and remote sensing, VOL. 58, NO. 12, DECEMBER 2020

[36] Li Liu , Yuebin Wang ,Junhuan Peng, and Antonio Plaza , DFLLR: Deep Feature Learning With Latent Relationship Embedding for Remote Sensing Image Retrieval, IEEE transactions on geoscience and remote sensing, VOL. 60, 2022

[37] Xinyue Li, Song Wei,Jian Wang , Yanling Du, and Mengying Ge , Adaptive Multi-Proxy for Remote Sensing Image Retrieval, Remote Sens.,14,5615(2022).

[38] Shawn D. Newsam and Chandrika Kamath , Retrieval Using Texture Features in High Resolution Multi-spectral Satellite Imagery , UCRL-CONF-201981(2004)

[39] [Chandani Joshi , Saurabh Mukherjee, Empirical Analysis of SIFT, Gabor and Fused Feature Classification Using SVM for Multispectral Satellite Image Retrieval, Fourth International Conference on Image Information Processing (ICIIP) (2017)

[40] Jinmika Wijitdechakul et.al., UAV-based Multispectral Aerial Image Retrieval using Spectral Feature and Semantic Computing , International Electronics Symposium on Knowledge Creation and Intelligent Computing (IES-KCIC)(2017)

[41] Devulapalli Sudheer, Rajakumar Krishnan, Multiscale Texture Analysis and Color Coherence Vector Based Feature Descriptor for Multispectral Image Retrieval,, Advances in Science, Technology and Engineering Systems Journal Vol. 4, No. 6, 270-279 (2019)

[42] Xuelei Chen, Cunyue Lu, an end-to-end adversarial hashing method for unsupervised multispectral remote sensing image retrieval, ICIP 2020

[43] B. Sathiyaprasad, B. Satheesh Kumar, Multi Spectral Image Retrieval in Remote Sensing Big Data using Fast Recurrent Convolutional Neural Network , 2022 International Conference for Advancement in Technology (ICONAT) Goa, India. Jan 21-22, 2022

[44] Gran˜a n, Miguel A. Veganzones , An end member-based distance for content based hyperspectral image retrieval Manuel , Pattern Recognition 45 ,3472–3489(2012)

[45] Miguel A. Veganzones, Mihai Datcu and Manuel Gra˜na1,Dictionary based hyperspectral imageretrieval, In Proceedings of the 1st International Conference on Pattern Recognition Applications and Methods, pages426-432(2012)

[46] Miguel Angel Veganzones, and Manuel Graña, , A Spectral/Spatial CBIR System for Hyperspectral Images, IEEE Journal of selected topics in applied earth observations and remote sensing, VOL. 5, NO. 2, APRIL 2012

[47] Fatih Ömrüuzun , Begüm Demir, Lorenzo Bruzzone, Yasemin Yardımcı Çetin1, Content based hyperspectral image retrieval using bag of endmembers image descriptors (2015)

[48] Lu Chen, Jing Zhang, Xi Liang, Jiafeng Li, Li Zhuo , Deep Spectral-Spatial Feature Extraction Based on DCGAN for Hyperspectral Image Retrieval , 2017 IEEE 15th Intl Conf on Dependable, Autonomic and Secure Computing

[49] Jing Zhang, Lu Chen, Li Zhuo, Xi Liang and Jiafeng Li, An Efficient Hyperspectral Image Retrieval Method: Deep Spectral-Spatial Feature Extraction with DCGAN and Dimensionality Reduction Using t-SNE-Based NM Hashing, Remote Sens. 2018, 10, 271; doi:10.3390/rs10020271(2018)

[50] Olfa Ben-Ahmed , Thierry Urruty , Noël Richard and Christine Fernandez-Maloigne , Toward Content-Based Hyperspectral Remote Sensing Image Retrieval (CB-HRSIR): A Preliminary Study Based on Spectral Sensitivity Functions , Remote Sens. 2019, 11, 600; doi:10.3390/rs11050600(2019)

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7
DOI: https://doi.org/10.17762/ijritcc.v11i7.7831
***Article Received**: 16 April 2023 **Revised**: 19 June 2023 **Accepted**: 02 July 2023*

TABLE VII. SUMMARY OF RETRIEVAL RESULTS FOR AERIAL IMAGES

Method	Precision	Recall	MAP	ANMRR
Feature representation using hashing				
Partial Randomness Hashing [3]	-	-	0.5202	-
An Unsupervised Multicode Hashing Method [4]	-	65.29	-	-
Low-Rank Hypergraph Hashing [5]	-	-	0.7333	-
Cohesion Intensive Deep Hashing [6]	-	-	0.9858	-
Metric-Learning based Deep Hashing Network[7]	-	-	0.926	-
Using Probabilistic Latent Semantic Hashing[8]	63.15	60.09	-	-
Feature representation using low level representation				
Improved color texture descriptors[12]	0.60	-	-	-
Global Morphological Texture Descriptors[13]	-	-	-	0.64
Multiscale Texture Features [14]	74.29	-	-	-
Advanced Local Binary Patterns [15]	-	76.17	-	-
Multi-scale local ternary pattern[16]	82.65	-	-	-
Visual salient point features[20]	24.96	37.98	-	-
Feature representation using middle level representation				
Using Local Invariant Features[23]	-	-	-	0.8079
An improved Bag-of-Words framework [25]	0.67	-	-	-
Feature representation using high level representation				
Aggregated Deep Local Features [27]	0.933	-	-	-
Unsupervised Feature Learning & Collaborative Affinity Metric Fusion[28]	0.7657	-	-	-
A Discriminative Feature Learning Approach [29]	-	-	0.840	0.081
Siamese graph convolutional network [30]	-	-	81.79	0.21
Triplet Deep Metric Learning Network[31]	-	-	0.9955	0.0223
Eagle-Eyed Multitask CNNs [33]	-	-	99.51	0.0203
Coarse-to-Fine Deep Metric Learning [34]	-	87.1	-	-
Deep Metric Learning With GAN Regularization [35]	-	-	0.9885	0.0042
Deep Feature Learning With Latent Relationship Embedding [36]	-	-	0.9502	0.0292
Adaptive Multi-Proxy [37]	-	-	65.32	-

TABLE VIII. SUMMARY OF RETRIEVAL RESULTS FOR MULTISPECTRAL IMAGES

Method	Precision	Recall	MAP	ANMRR
Retrieval Using Texture Features [38]	0.8202	-	-	-
Spectral Feature and Semantic Computing [40]	68.6	-	-	-
Multiscale Texture Analysis & CCV Based Feature Descriptor [41]	-	-	-	0.2215
An End-To-End Adversarial Hashing Method [42]	-	-	0.6827	-
Fast Recurrent Convolutional Neural Network [43]	80	70	-	-

TABLE IX. SUMMARY OF RETRIEVAL RESULTS FOR HYPERSPECTRAL IMAGES

Method	Precision	Recall	MAP	ANMRR
Dictionary based [45]	-	-	-	0.019
A Spectral/Spatial CBIR System [46]	-	-	-	0.033
Using Bag of Endmembers Image Descriptors [47]	77.54	74.70	-	-
Deep Spectral-Spatial Feature Extraction Based on DCGAN [48]	0.8649	-	-	-
DCGAN & Dimensionality Reduction Using t-SNE-Based NM Hashing [49]	86.49	-	79.20	-
A Preliminary Study Based on Spectral Sensitivity Functions [50]	-	-	66.54	-