Large-Scale Remote Sensing Image Processing and Analysis

Xiao Bai
Beihang University

Content

Research Group Introduction

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Research Interests: Remote sensing/Hyperspectral data analysis, Vision computation, Image processing, Large-scale information retrieval.

School of Computer Science and Engineering of Beihang University is ranked by the Ministry of Science and Education as one of the top three computer science schools in China. Within the school there reside the State key Lab for Software Development Environment and the State key laboratory of Virtual Reality Technology and Systems. The school is proud of its academic staff including 3 members of the Chinese Academy of Sciences, 52 professors, 52 associate professors, 2 Chang Jiang Scholar, 3 professor of Recruitment Program of Global Experts and 4 part-time doctoral supervisors.

Laboratory Members:

The research team includes 5 teachers, 7 PhD students, 15 Master students. The team has published over 100 papers in the area of RS image processing and analysis, large-scale visual retrieval and visual computing and understanding in the past 5 years.

Background

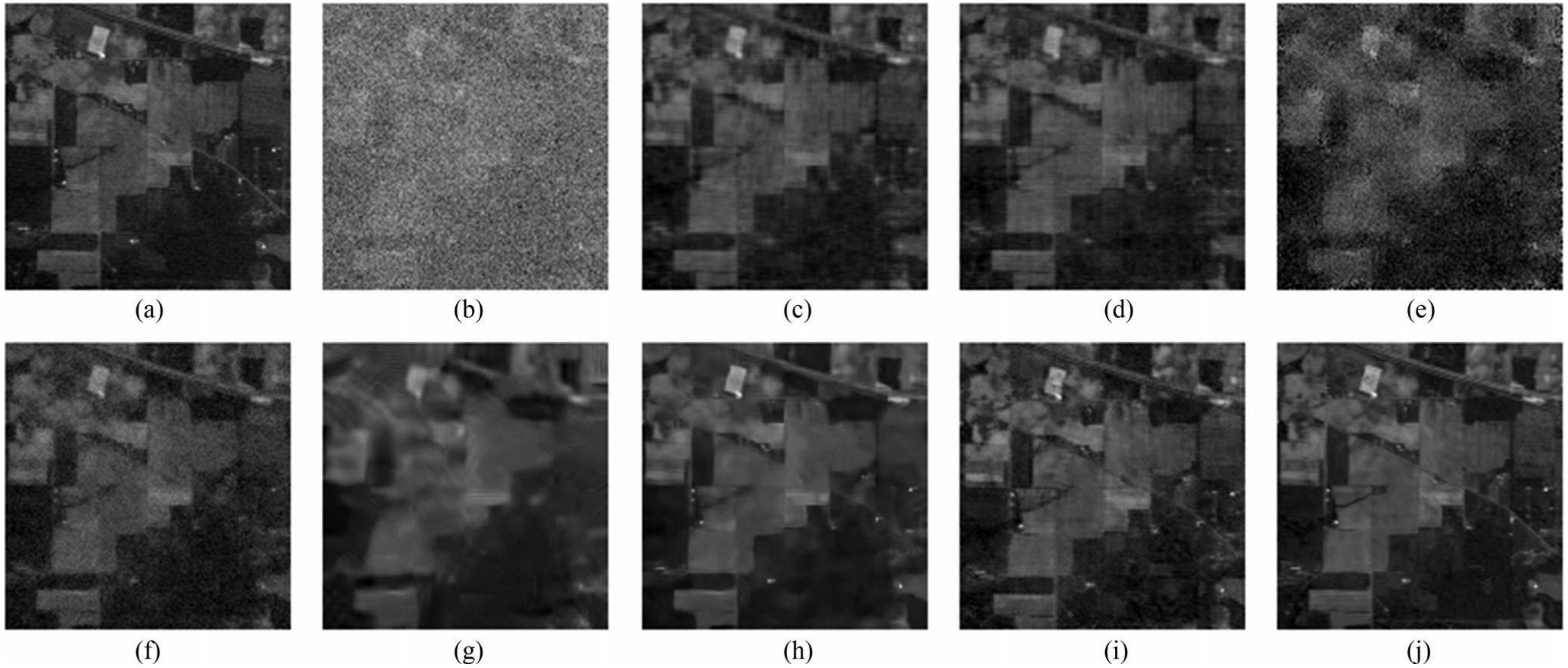
With the rapid development of remote sensing observation technologies, we have entered an era of remote sensing big data.

- **Large-Scale Data** ➡ The amount of remote sensing images has increased dramatically, due to the recent advances in satellite technology.
- **Data Quality** ➡ Noisy images, Low-resolution images, Mixed pixel images…
- **Data Tags** ➡ Most of the remote sensing images are untagged. Manual generation of tags is often time consuming.
- **Efficient Applications** ➡ Efficient algorithms for large-scale remote sensing images are highly demanded for practical applications.

Content

Image Enhancement—Denoising

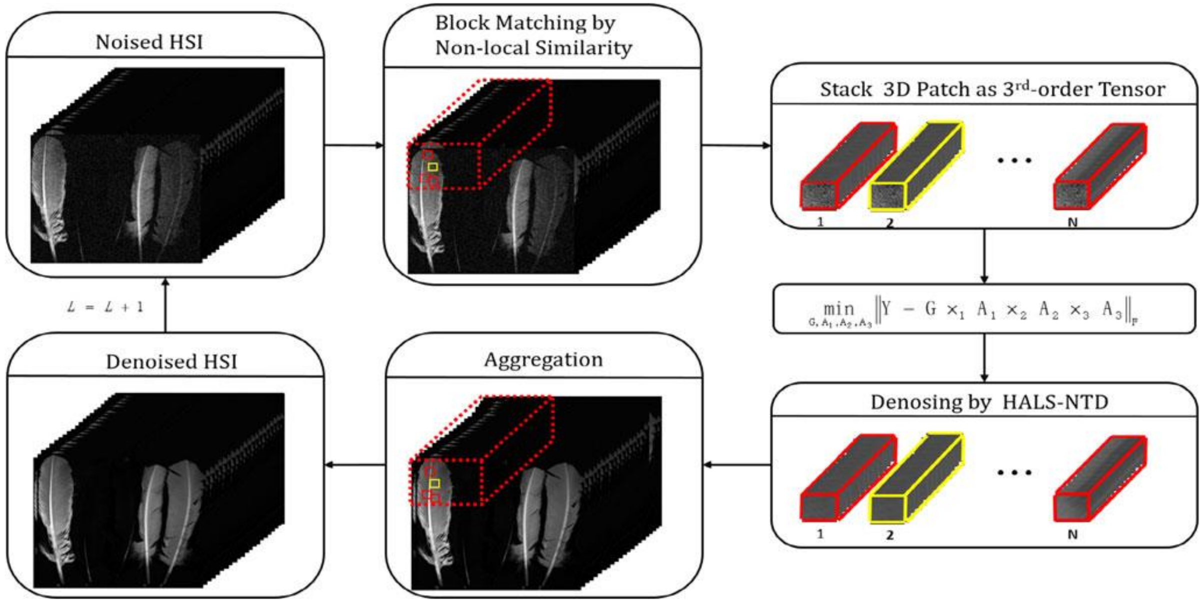
Nonnegative Tucker Decomposition for Hyperspectral Image Denoising



Conventional hyperspectral imaging process suffers from issues such as limited illumination and short sensing time, which introduce noises into the image acquisition step.

Image Enhancement—Denoising

Nonnegative Tucker Decomposition for Hyperspectral Image Denoising



PERFORMANCE COMPARISON OF THE COMPETING METHODS ON THE INDIAN PINES DATASET.

Methods	$\sigma = 20$			$\sigma = 30$			$\sigma = 40$			$\sigma = 50$		
	PSNR	SSIM	FSIM	PSNR	SSIM	FSIM	PSNR	SSIM	FSIM	PSNR	SSIM	FSIM
Noisy	22.134	0.394	0.730	18.617	0.117	0.407	16.113	0.081	0.352	14.175	0.054	0.302
LRTA [26]	38.640	0.902	0.936	36.543	0.854	0.905	34.832	0.826	0.896	34.328	0.826	0.889
PARAFAC [25]	38.877	0.904	0.933	35.225	0.830	0.891	29.536	0.582	0.777	27.479	0.463	0.716
BwK-SVD [13]	30.584	0.678	0.863	28.947	0.582	0.775	28.129	0.529	0.760	27.349	0.486	0.745
K-SVD [16]	35.329	0.836	0.893	33.533	0.769	0.860	33.459	0.781	0.867	22.116	0.203	0.535
BwBM3D [14]	36.736	0.867	0.884	35.174	0.833	0.863	33.358	0.794	0.854	33.002	0.774	0.838
BM4D [17]	38.642	0.906	0.917	36.826	0.874	0.898	35.105	0.845	0.892	34.069	0.819	0.881
SPA+LR [18]	41.143	0.931	0.951	38.301	0.903	0.930	36.328	0.838	0.899	35.523	0.869	0.914
Ours	**41.937**	**0.946**	**0.975**	**39.026**	**0.912**	**0.939**	**37.012**	**0.862**	**0.917**	**35.972**	**0.893**	**0.926**

- Fan Xu, **Xiao Bai**, Jun Zhou: Non-local similarity based tensor decomposition for hyperspectral image denoising. ICIP 2017: 1890-1894
- **Xiao Bai**, Fan Xu, Lei Zhou, Yan Xing, Lu Bai and Jun Zhou. "Nonlocal similarity based nonnegative tucker decomposition for hyperspectral image denoising". IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, Vol. 11, No. 3, pages 701-712, 2018.

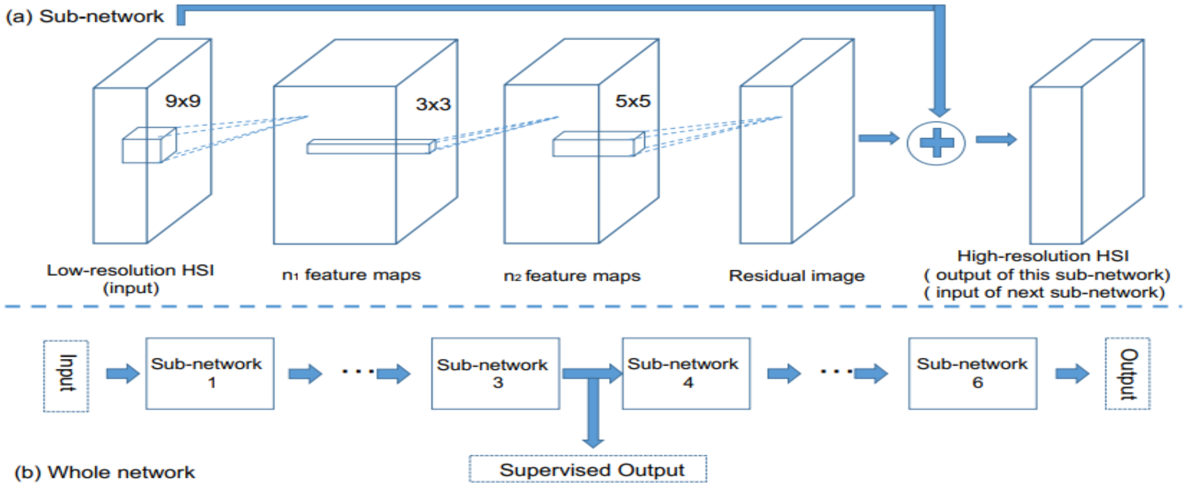
Image Super-Resolution

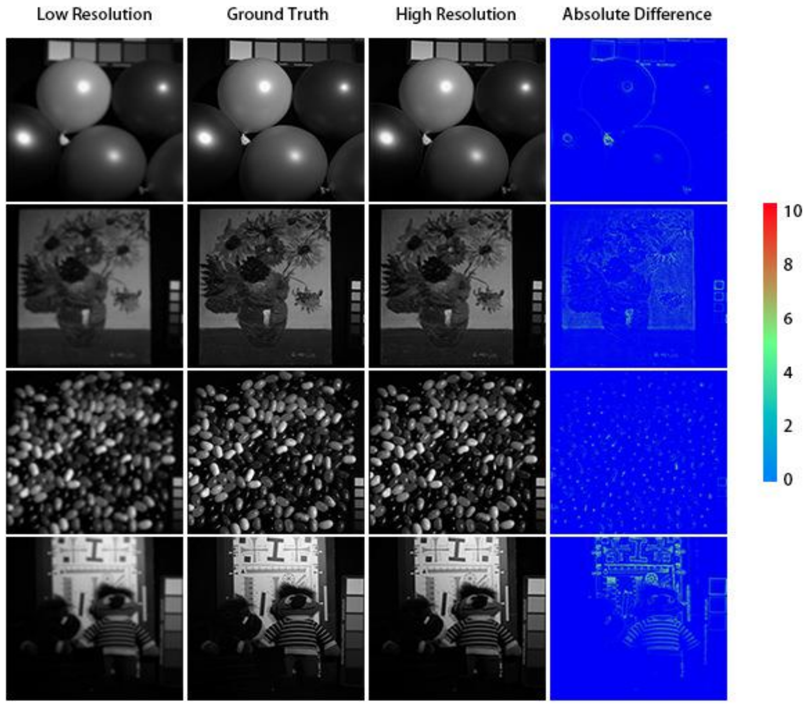
low-resolution image → high-resolution image

- Civil : GF-2 geometric resolution 1-4 m, google map’s resolution 0.39 m
- A high-quality remote sensing image is significant to applications

Image Super-Resolution

low-resolution image ➡ high-resolution image

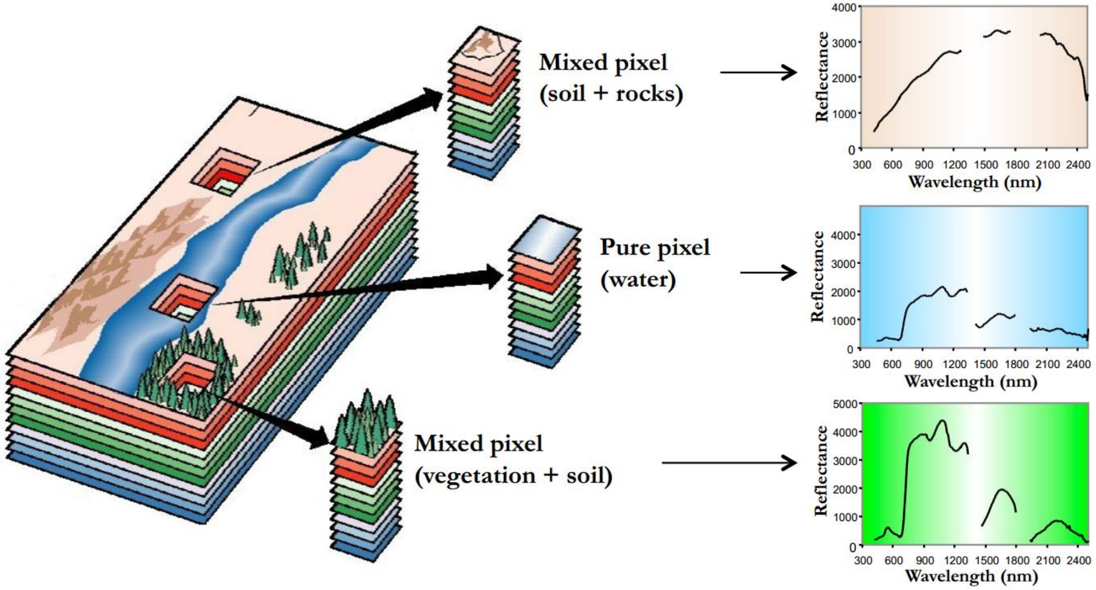


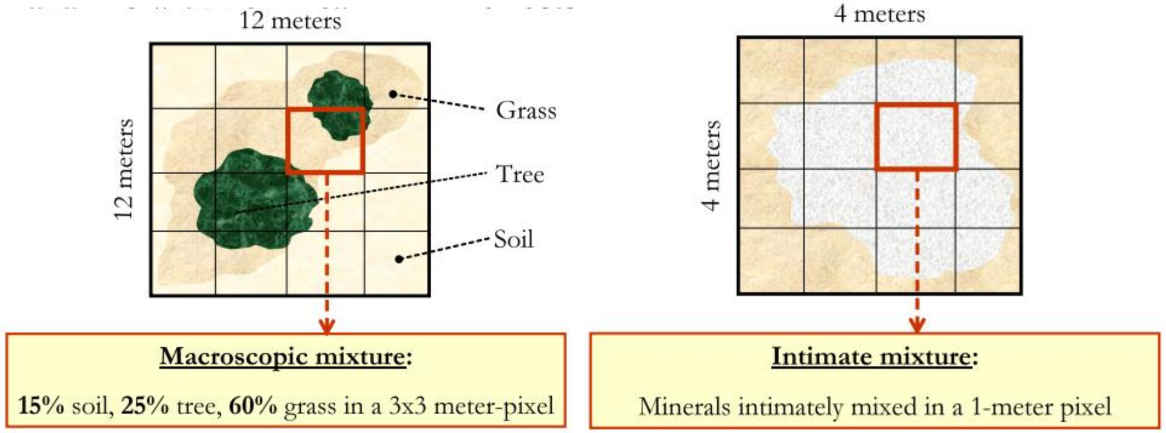


- Chen Wang, Yun Liu, **Xiao Bai**, Wenzhong Tang, Peng Lei, Jun Zhou: Deep Residual Convolutional Neural Network for Hyperspectral Image Super-Resolution. ICIG (3) 2017: 370-380

Hyperspectral Unmixing

Mixed pixels are frequent in remotely sensed hyperspectral images due to insufficient spatial resolution of the imaging spectrometer, or due to intimate mixing effects.



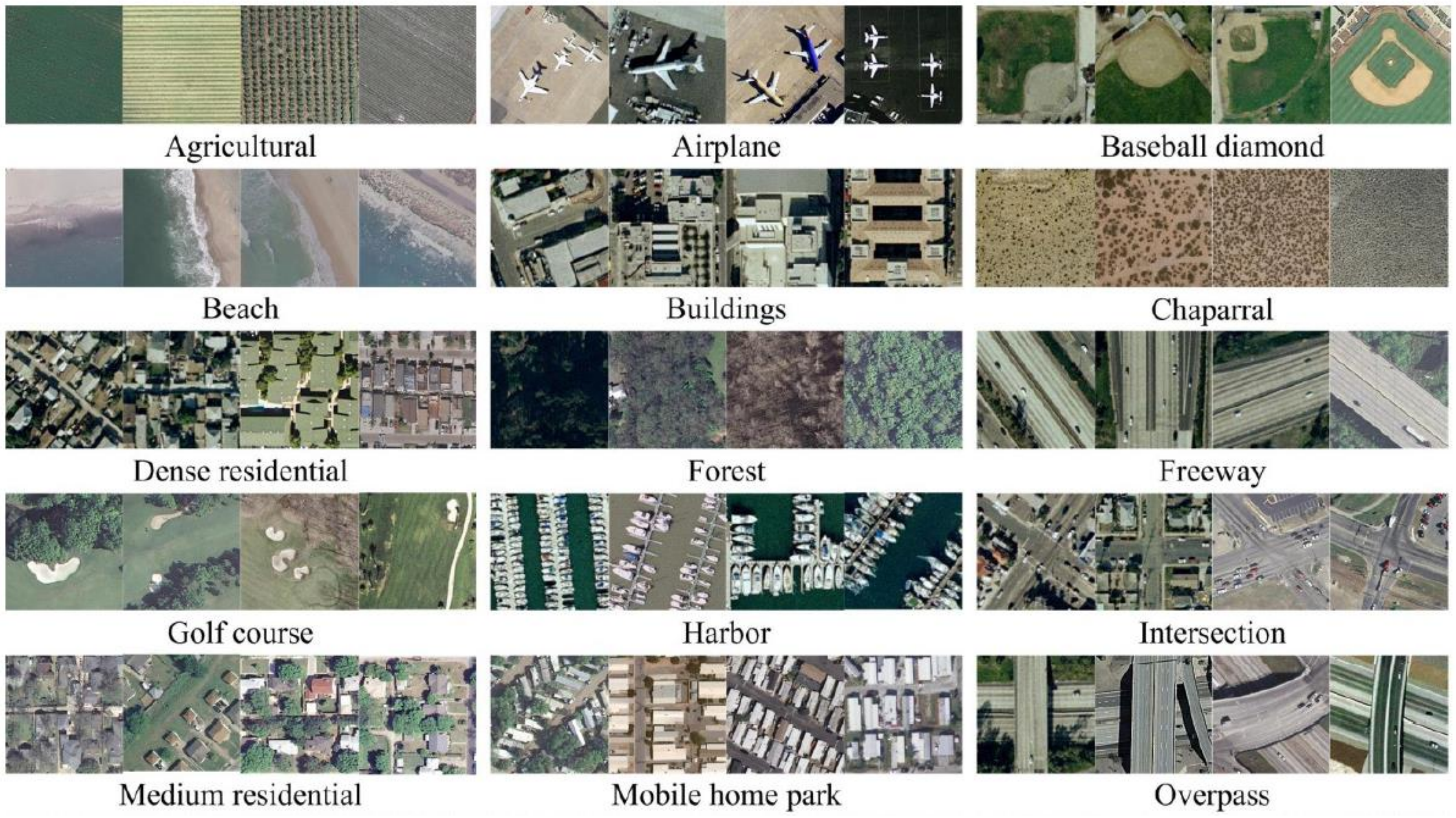


- Lei Tong, Jun Zhou, Yuntao Qian, **Xiao Bai**, and Yongsheng Gao. "Nonnegative matrix factorization based hyperspectral unmixing with partially known endmembers". IEEE Transactions on Geoscience and Remote Sensing, Vol. 54, No. 11, pages 6531-6544, 2016.

Content

Remote Sensing Image Classification

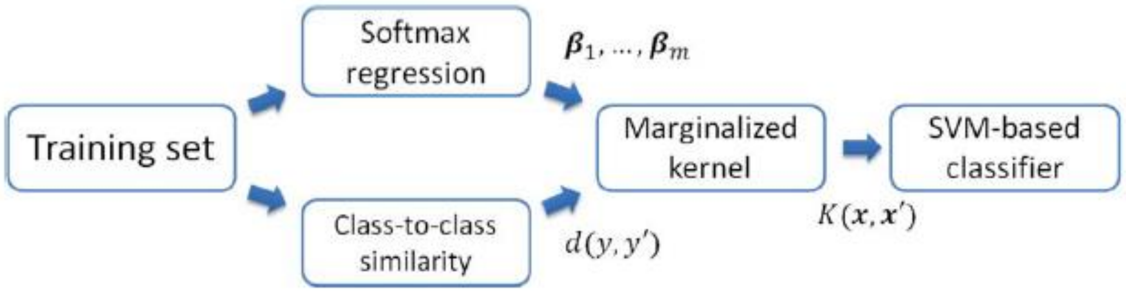
Due to the large volume of untagged remote sensing images, the manual generation of tags is often time consuming and becomes especially prohibitive.



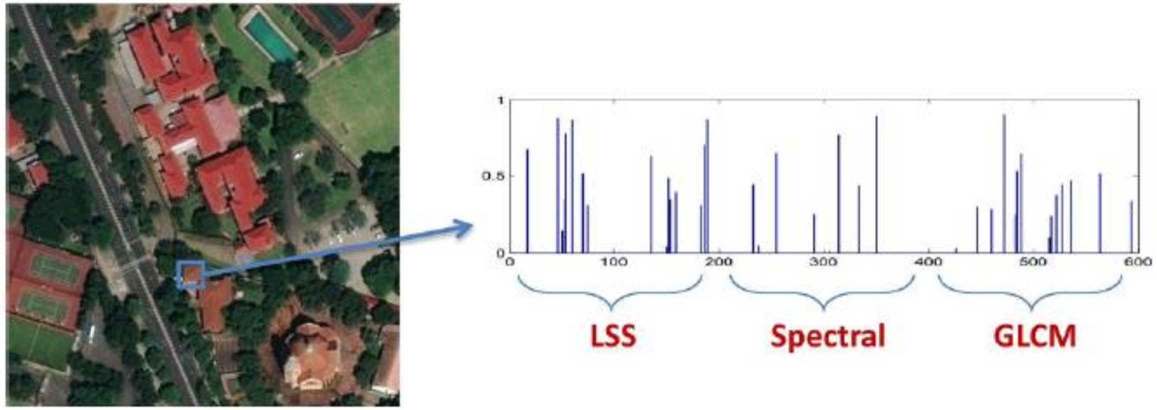
Remote sensing image classification technology is significant and important.

Remote Sensing Image Classification

Object Classification via Feature Fusion Based Marginalized Kernels



1. We use the SoftMax regression to model the probabilities of each sample object belonging to the object classes.
2. We introduce an approximate method for calculating the class-to-class similarities between different classes.
3. The obtained fusion and similarity information are integrated into a marginalized kernel to build a support vector machine classifier.

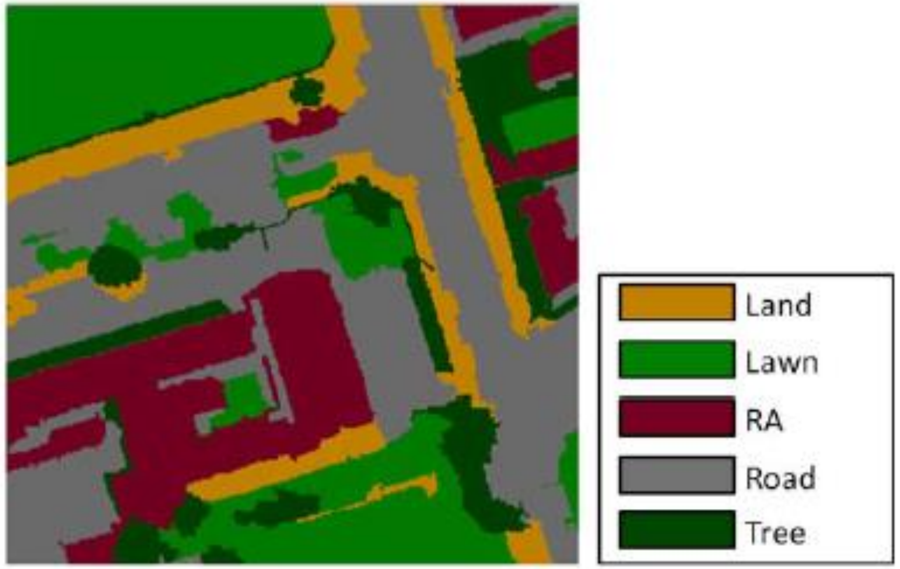


Example of object representation with three types of features concatenated. Local self-similarity (LSS) and gray-level co-occurrence matrices (GLCMs) stand for shape and texture features, respectively.

- **Xiao Bai**, Chuntian Liu, Peng Ren, Jun Zhou, Huijie Zhao, Yun Su: Object Classification via Feature Fusion Based Marginalized Kernels. IEEE Geosci. Remote Sensing Lett. 12(1): 8-12 (2015)

Remote Sensing Image Classification

Object Classification via Feature Fusion Based Marginalized Kernels

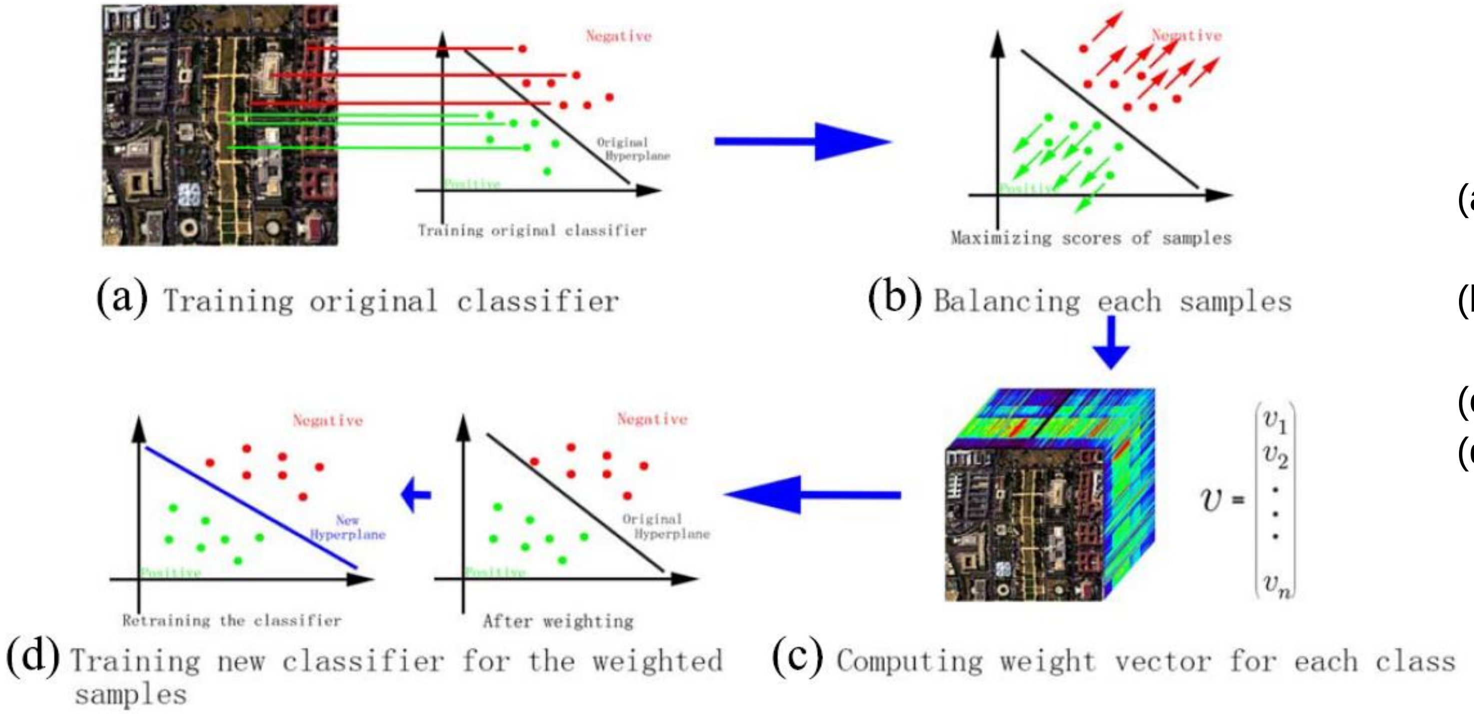


Classification result

- **Xiao Bai**, Chuntian Liu, Peng Ren, Jun Zhou, Huijie Zhao, Yun Su: Object Classification via Feature Fusion Based Marginalized Kernels. IEEE Geosci. Remote Sensing Lett. 12(1): 8-12 (2015)

Remote Sensing Image Classification

Hyperspectral Image Classification

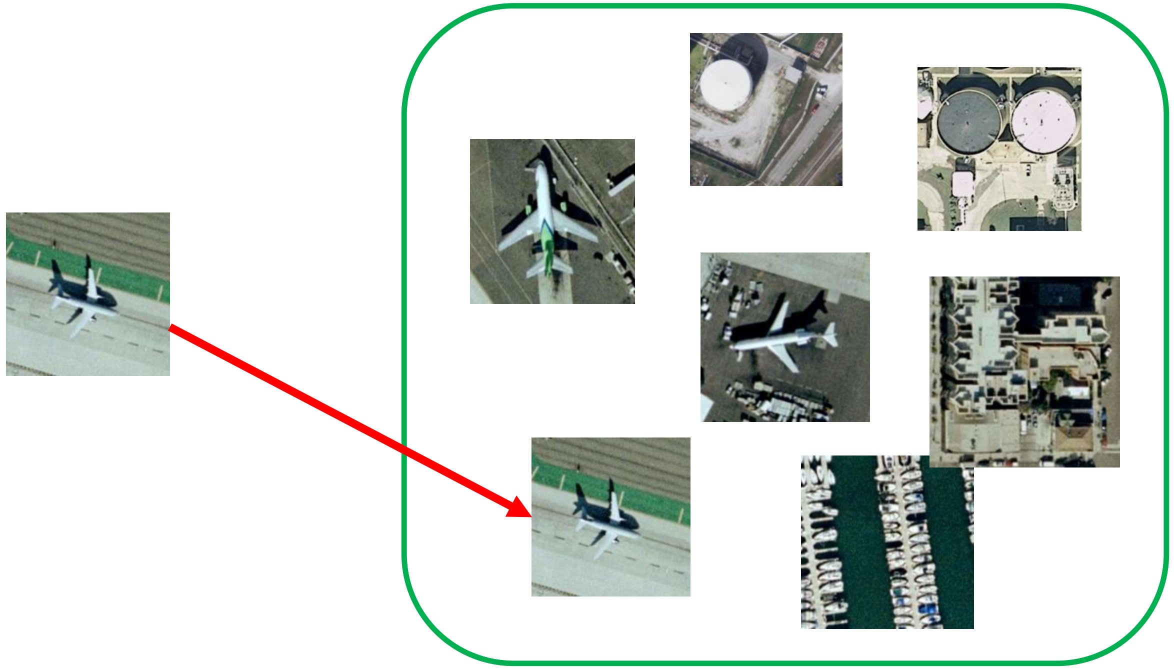


(a) Training the initial classifier for each class by using traditional SVM.
(b) Balancing the spectral bands for each sample by maximizing the modified SVM classification scores.
(c) Computing the spectral weight vector for each class.
(d) Training new classifiers by using weighted samples.

- Cheng Yan, **Xiao Bai**, Peng Ren, Lu Bai, Wenzhong Tang, Jun Zhou: Band Weighting via Maximizing Interclass Distance for Hyperspectral Image Classification. IEEE Geosci. Remote Sensing Lett. 13(7): 922-925 (2016)

Content

Large-Scale Retrieval



Fast and accurate retrieval method for large-scale remote sensing image datasets is highly demanded.

- The amount of remote sensing images has increased dramatically, due to the recent advances in satellite technology.
- The efficiency of many traditional methods can’t meet the requirements of practical application.

Binary Coding

Hashing-based efficient retrieval

Data 1	-1	+1	-1	+1	......	-1	48 bits
Data 2	+1	-1	+1	+1	......	+1	48 bits
Data N	-1	-1	+1	-1	......	+1	48 bits

10^{-9} s to calculate Hamming distance

Store **1.8 billion** data with **10G** RAM

- ➢ Transform remote sensing images into binary codes
- ➢ The Hamming distances between binary codes preserve the pairwise similarities of the data
- ➢ Significantly reduce the storage space for large-scale data
- ➢ Calculating the Hamming distance is very fast in computer

Binary Coding

$$\boxed{H(x_i) = [h_1(x_i), h_2(x_i), \ldots, h_K(x_i)] \in \{0,1\}^K}$$

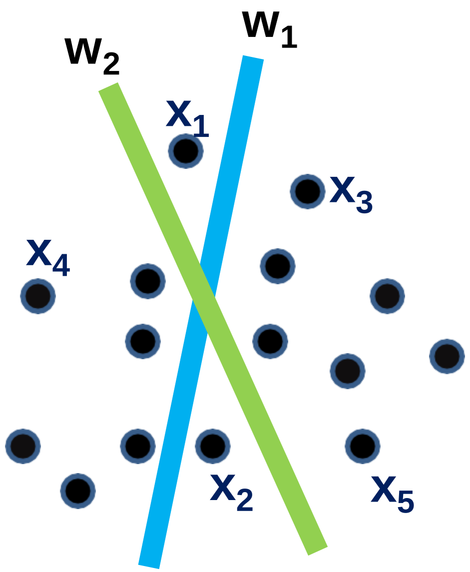
… 110110 010110 … 001000 000001

Hamming distance: 1 < 4

1. Learn a set of hash functions $h_i(\cdot)$ to convert input images to binary codes.
2. Organize all the codes in a hash table.
3. Return all images within a small radius of query in database using hash table.

Locality Sensitive Hashing

Locality Sensitive Hashing



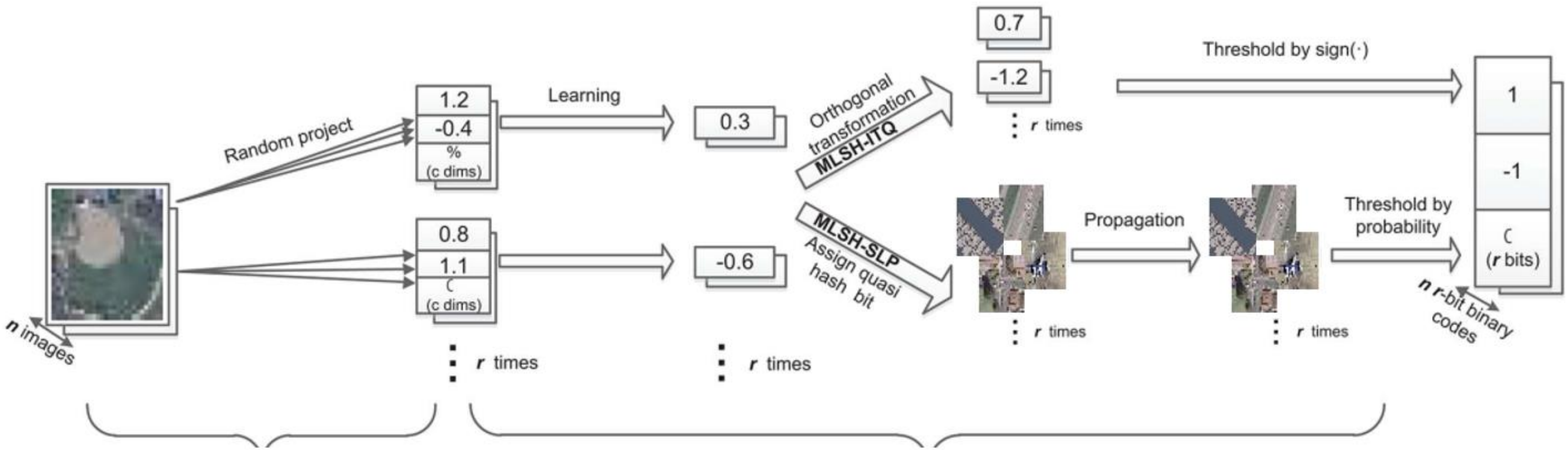
X	x_1	x_2	x_3	x_4	x_5
w_1	0	1	1	0	1
w_2	1	0	1	0	1
…	…	…	…	…	…
w_m	…	…	…	…	…
	010…	100…	111…	001…	110…

A simple LSH hash functions: $h_k(x) = \mathrm{sgn}(w_k^T x)$

- M. Datar, N. Immorlica, P. Indyk, and V. Mirrokni, "Locality-sensitive hashing scheme based on p-stable distributions," in Annual Symposium on Computational Geometry, 2004.

Large-Scale Retrieval

Data-Dependent Hashing Based on p-Stable Distribution



➢ **Xiao Bai**, Haichuan Yang, Jun Zhou, Peng Ren, Jian Cheng: Data-Dependent Hashing Based on p-Stable Distribution. IEEE Trans. Image Processing 23(12): 5033-5046 (2014)

Large-Scale Retrieval

Data-Dependent Hashing Based on p-Stable Distribution

- **Unsupervised Hashing For Preserving Euclidean Distance**

quantization error:

$$\sum_{i}^{n}\sum_{k}^{r}(\mathrm{sign}(U_k^T v_i) - U_k^T v_i)^2$$

objective function:

$$\arg\min_{R} \|\mathrm{sign}((UR)^T V) - (UR)^T V\|_F^2$$

- **Supervised Hashing By Incorporating Semantic Similarity**

supervised semantic similarity:

$$S_{ij} = \begin{cases} 1, & \mathrm{L}(i) = \mathrm{L}(j); \\ 0, & \text{otherwise.} \end{cases}$$

objective function:

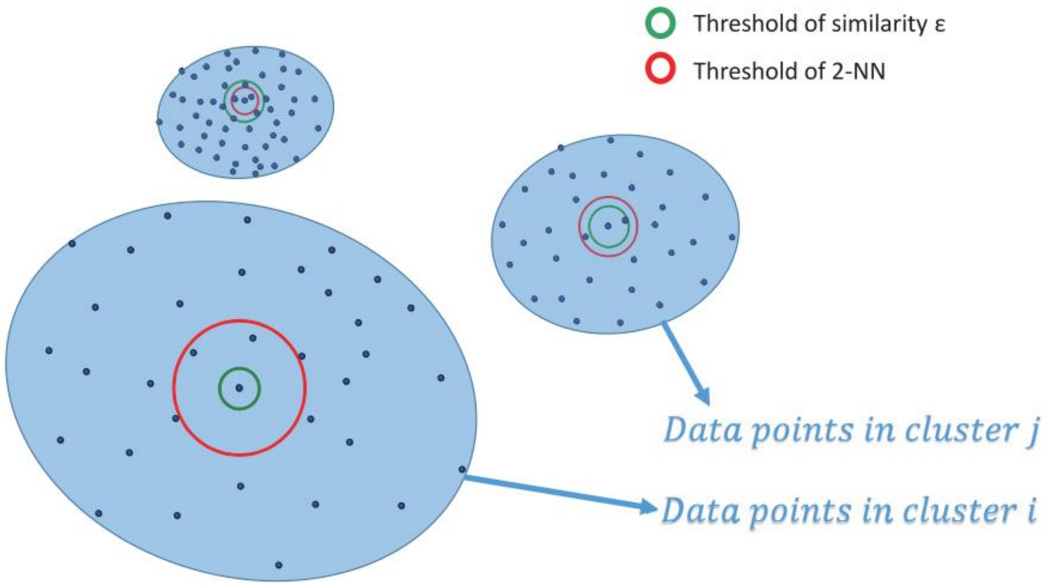
$$\arg\min_{Y} \sum_{i,j} S_{ij} \|y_i - y_j\|^2$$

$$\text{subject to: } y_i \in \{0, 1\}^{r\times 1}, \sum_{i}^{n} y_i = \frac{n}{2}\mathbf{1}_r$$

➢ **Xiao Bai**, Haichuan Yang, Jun Zhou, Peng Ren, Jian Cheng: Data-Dependent Hashing Based on p-Stable Distribution. IEEE Trans. Image Processing 23(12): 5033-5046 (2014)

Large-Scale Retrieval

Adaptive Hash Retrieval with Kernel based Similarity



Since the similarity or distance to the nearest neighbors varies considerably for different data samples, simple thresholding on the similarity function returns different numbers of neighbors.

- **Xiao Bai**, Cheng Yan, Haichuan Yang, Lu Bai, Jun Zhou, Edwin Robert Hancock: Adaptive hash retrieval with kernel based similarity. Pattern Recognition 75: 136-148 (2018)

Large-Scale Retrieval

Adaptive Hash Retrieval with Kernel based Similarity

We present a novel adaptive similarity measure which is consistent with k-nearest neighbor search, and prove that it leads to a valid kernel if the original similarity function is a kernel function.

1. We use normalized Gaussian kernel to construct a new similarity function:

$$\kappa(\mathbf{x}_i, \mathbf{x}_j) = \exp(-(d(\mathbf{x}_i, \mathbf{x}_j))^2 / 2\sigma^2)$$

2. We propose kernel reconstructive hashing that preserves the similarity defined by an arbitrary kernel using a compact binary code.

$$\min \sum_{\mathbf{x}_i, \mathbf{x}_j \in X} (\langle \hat{\mathbf{x}}_i, \hat{\mathbf{x}}_j \rangle - \kappa(\mathbf{x}_i, \mathbf{x}_j))^2$$

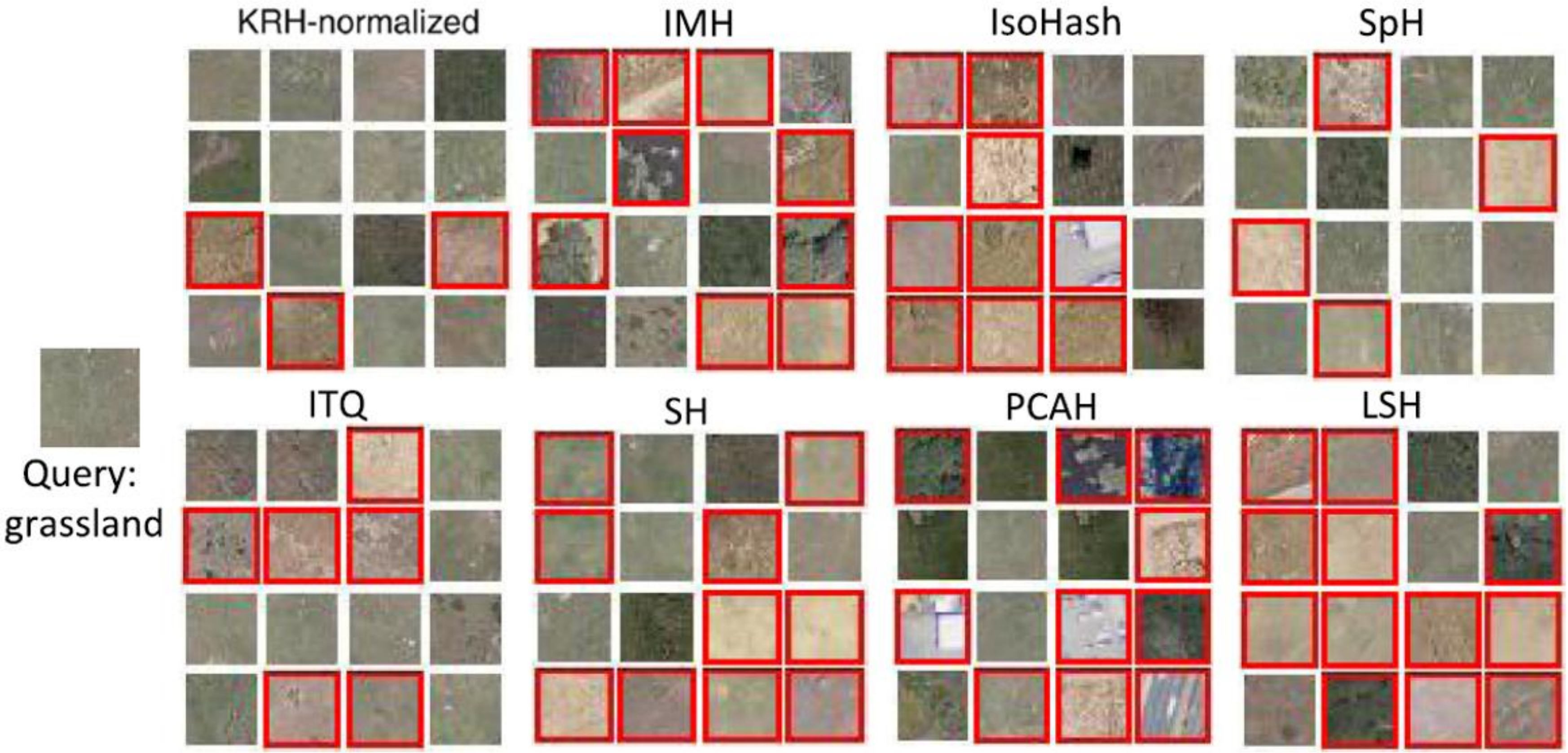
Our objective formulation is learning a set of r hash functions which generate the binary code of x_i as a vector

$$\tilde{\mathbf{x}}_i = [h_1(\mathbf{x}_i), h_2(\mathbf{x}_i), \ldots, h_r(\mathbf{x}_i)].$$

➢ **Xiao Bai**, Cheng Yan, Haichuan Yang, Lu Bai, Jun Zhou, Edwin Robert Hancock: Adaptive hash retrieval with kernel based similarity. Pattern Recognition 75: 136-148 (2018)

Large-Scale Retrieval

Adaptive Hash Retrieval with Kernel based Similarity



- **Xiao Bai**, Cheng Yan, Haichuan Yang, Lu Bai, Jun Zhou, Edwin Robert Hancock: Adaptive hash retrieval with kernel based similarity. Pattern Recognition 75: 136-148 (2018)

Thanks for Your Attention!