MULTISOURCE REMOTE SENSING DATA CLASSIFICATION USING DEEP HIERARCHICAL RANDOM WALK NETWORKS

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Abstract

In this paper, collaborative classification of hyperspectral imagery (HSI) and light detection and ranging (LiDAR) data is investigated using an effective hierarchical random walk networks (HRWN). The proposed HRWN jointly optimizes a dual-tunnel convolution neural network (CNN) architecture capturing spectral and spatial features of HSI and a pixelwise affinity branch preserving spatial smoothness via a novel hierarchical random walk layer.

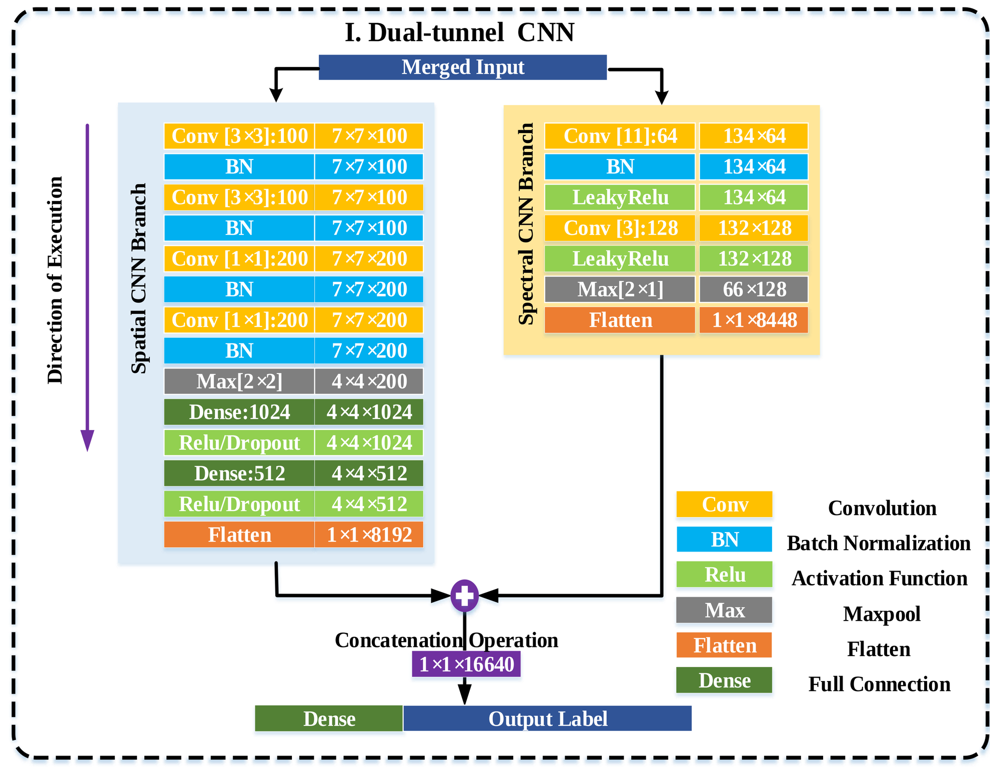
Motivation

- ➢A Analyze spatial and spectral feartures of HSI and LiDAR data by a dual-tunnel CNN.
- ➢A pixel affinity matrix capturing the similarity between classes and preserves spatial smoothness.
- ➢A random walk layer exploits spatial constraint and local seeds guidance into CNN.

Proposed Method

I: Dual-tunnel CNN branch that exploits classification potentials is firstly designed for merged HSI and LiDAR images. The joint spectral-spatial feature are extracted as

$$F_M = f(W \cdot (F_{ij}^{spe} \,\|\, F_{ij}^{spa}) + b)$$



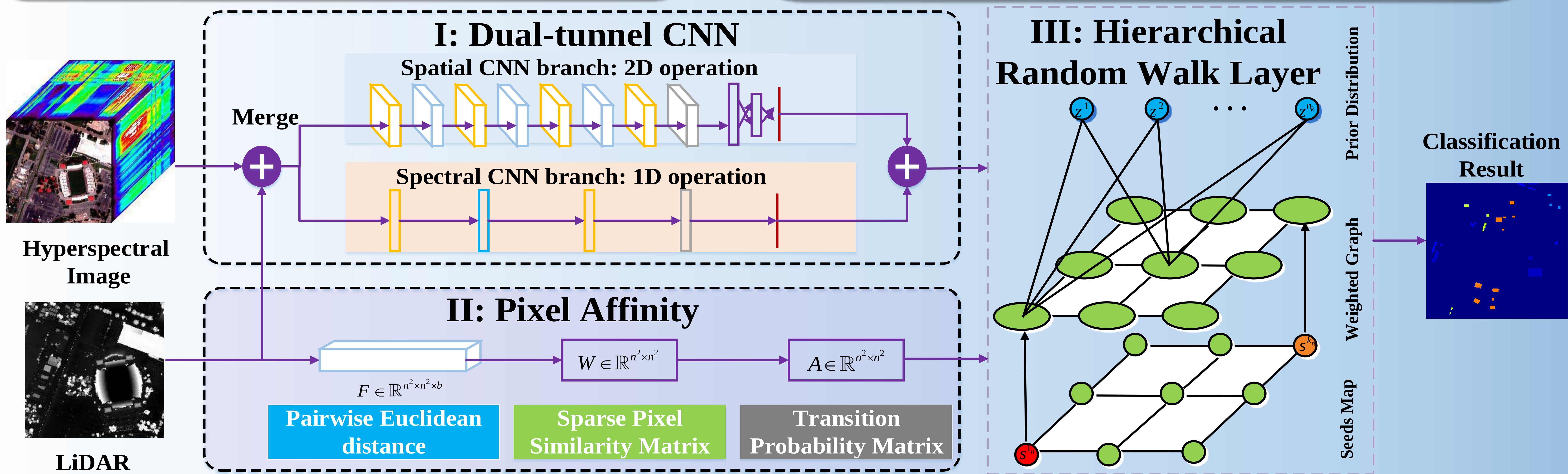
II: Pixel-level affinity branch is connected with the input LiDAR image for its elevation information, which is modeled as a weighted, undirected and connected graph. Then F is a sparse matrix storing Euclidean distance between each pixel and all its neighbors. Then the Euclidean loss layer F is optimized to predict the pixel similarity matrix W. Finally, the normalization matrix is applied to predict the ground truth pixel affinities A.

III: A novel random walk layer that merges the two branches to obtain classification map. Given the transition probability A on a graph with prior, the reaching probability that a random walker from a node reaching seed or prior node is

$$r_i^k = \sum_{j \sim i \in V} \frac{w_{ij} r_j^k}{d_i + \lambda g_i} + \frac{\lambda p_i^k}{d_i + \lambda g_i} + c s_i^k$$

Then the final classification result is

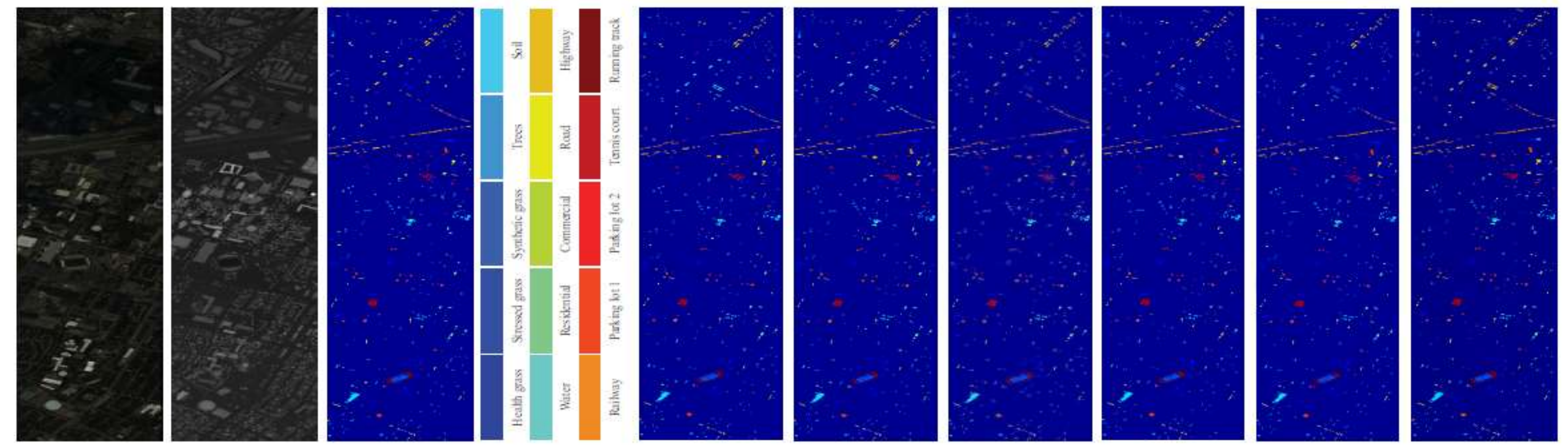
$$R_i = \arg\max_k r_i^k$$



Result

There are two real paired of HIS and LiDAR datasets acquired over Houston, USA and Trento, Italy are used to verify the performance of proposed method. To validate the effectiveness, the proposed HRWN is compared with several other classifiers, such as the standard SVM, ELM, recently-proposed CNN-PPF, two-branch CNN, the context CNN, and CNN-MRF.

Houston, USA



Trento, Italy

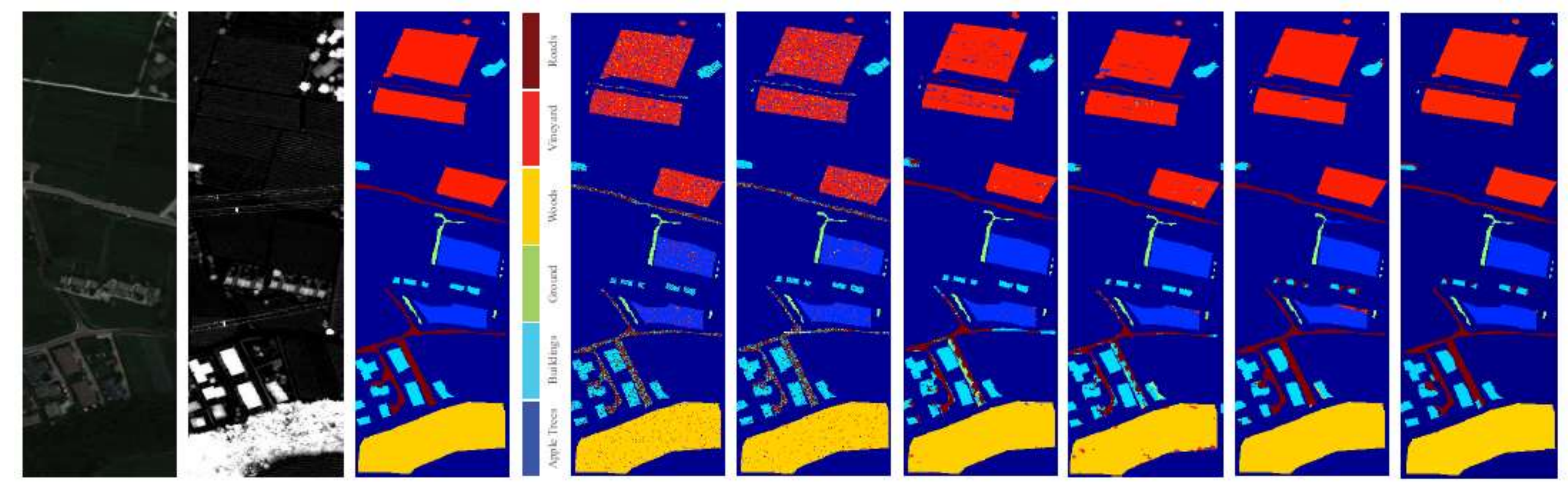


Table 1. Comparison of the Classification Accuracy (%) Using the Houston Data.

No.	Class(Train/Test)	Performance					
		SVM	ELM	CNN-PPF	TB-CNN	C-CNN	HRWN
1	Health grass (198/1053)	82.43	83.10	83.57	83.10	84.89	85.77
2	Stressed grass (190/1064)	82.05	83.70	98.21	84.10	87.40	80.64
3	Synthetic grass (192/505)	99.80	100.00	98.42	100.00	99.86	99.14
4	Tress (188/1056)	92.80	91.86	97.73	93.09	93.49	92.52
5	Soil (186/1056)	98.48	98.86	96.50	100.00	100.00	100.00
6	Water (182/143)	95.10	95.10	97.20	99.30	98.77	98.15
7	Residential (196/1072)	75.47	80.04	85.82	92.82	82.81	95.82
8	Commercial (191/1036)	46.91	68.47	56.51	82.34	78.78	97.51
9	Road (193/1059)	77.53	84.80	71.20	84.70	82.51	87.62
10	Highway (191/1036)	60.04	49.13	57.12	65.44	59.41	85.74
11	Railway (181/1054)	81.02	80.27	80.55	88.24	83.24	98.95
12	Parking lot 1 (192/1041)	85.49	79.06	62.82	89.53	92.13	97.89
13	Parking lot 2 (184/285)	75.09	71.58	63.86	92.28	94.88	91.04
14	Tennis court (181/247)	100.00	99.60	100.00	96.76	99.77	100.00
15	Running track (187/473)	98.31	98.52	98.10	99.79	98.79	100.00
	OA	80.49	81.92	83.33	87.98	86.90	93.45
	AA	83.37	84.27	83.21	90.11	89.11	94.25
	Kappa	0.7898	0.8045	0.8188	0.8698	0.8589	0.9292

Table 2. Comparison of the Classification Accuracy (%) Using the Trento Data.

No.	Class(Train/Test)	Performance					
		SVM	ELM	CNN-PPF	TB-CNN	C-CNN	HRWN
1	Apple trees (129/3905)	88.62	95.81	90.11	98.07	99.26	99.78
2	Buildings (125/2778)	94.04	96.97	83.34	95.21	86.81	90.35
3	Ground (105/374)	93.53	96.66	71.13	93.32	97.91	99.79
4	Woods (154/8969)	98.90	99.39	99.04	99.93	97.31	100.00
5	Vineyard (184/10317)	88.96	82.24	99.37	98.78	99.82	100.00
6	Roads (122/3525)	91.75	86.52	89.73	89.98	84.63	95.97
	OA	92.77	91.32	94.76	97.92	96.11	98.62
	AA	92.63	92.93	88.97	96.19	94.29	97.65
	Kappa	0.9585	0.9042	0.9304	0.9681	0.9481	0.9815

Reference

1. Xiaodong Xu,Wei Li, Qiong Ran, Qian Du, Lianru Gao, and Bing Zhang, “Multisource remote sensing data classification based on convolutional neural network,” IEEE Transactions on Geoscience and Remote Sensing, vol. PP, no. 99, pp. 1–13, 2018.
2. Leo Grady, “Random walks for image segmentation,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 28, no. 11, pp. 1768–1783, 2006.