A Prior Instruction Representation Framework for Remote Sensing Image-text Retrieval

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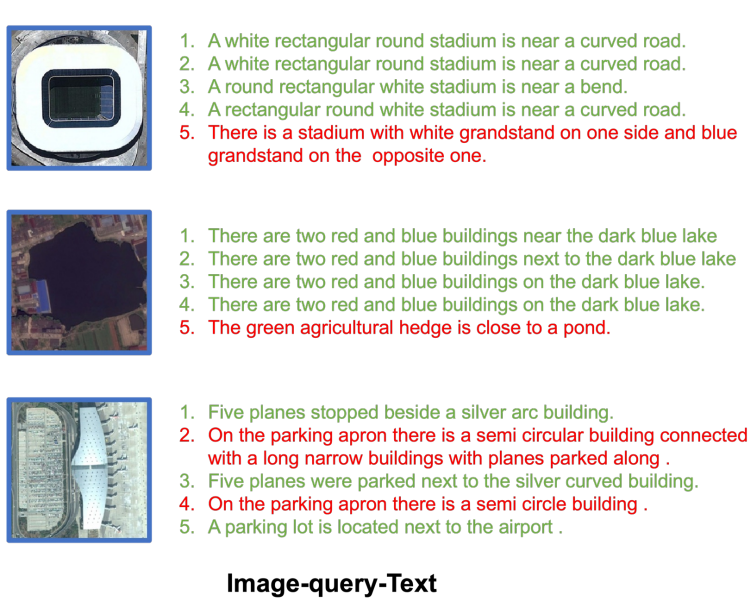
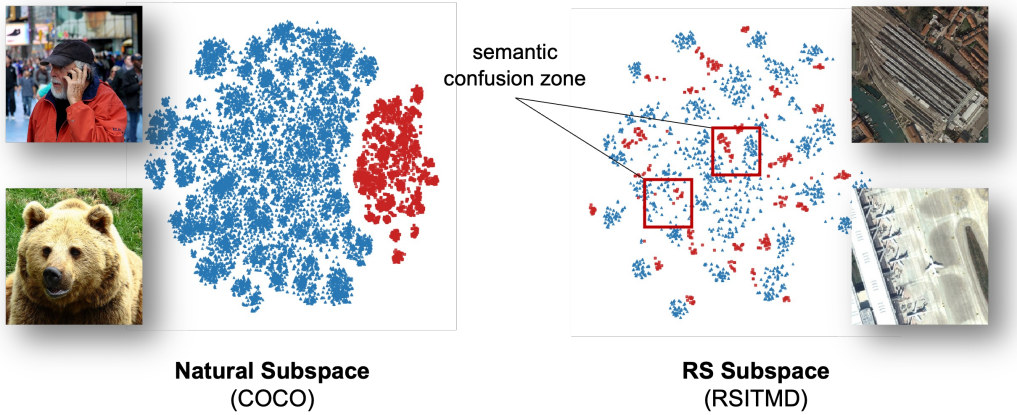
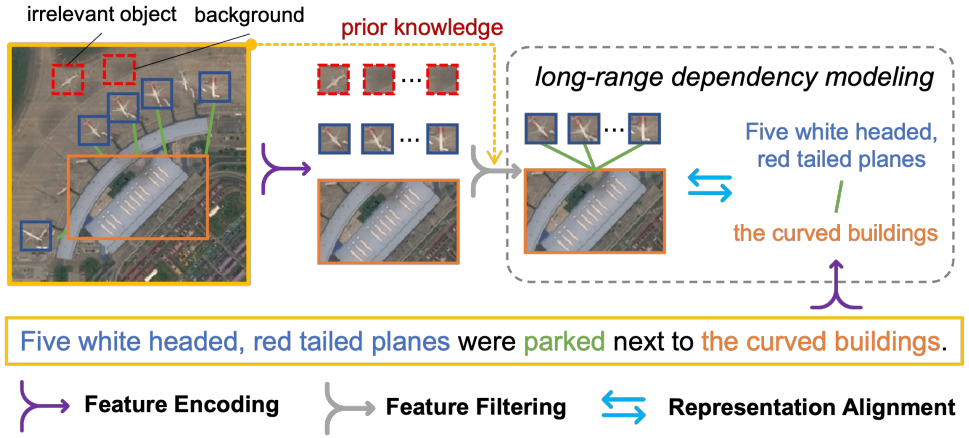




(a) Subspace Comparison



(b) Pipeline of PIR (Ours)

Problem

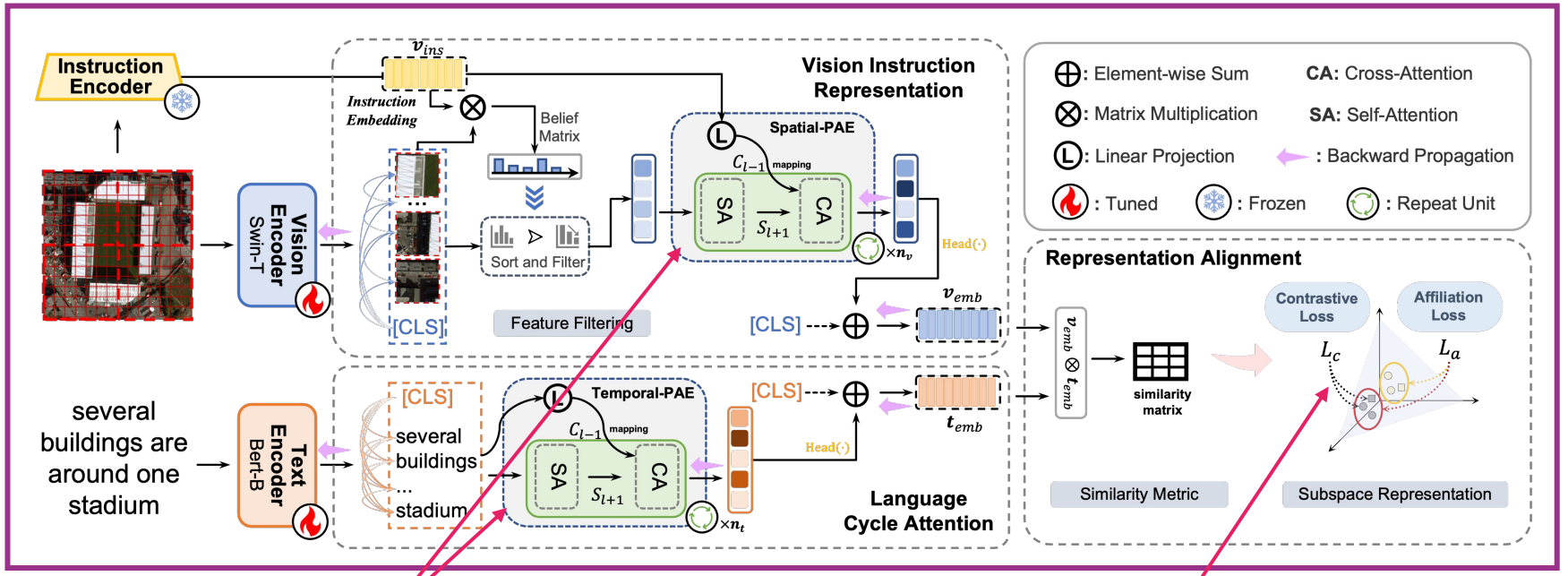
Unlike natural images, small–scale objects in remote sensing images are more prone to the interference of semantic noise, such as background, irrelevant objects, etc.

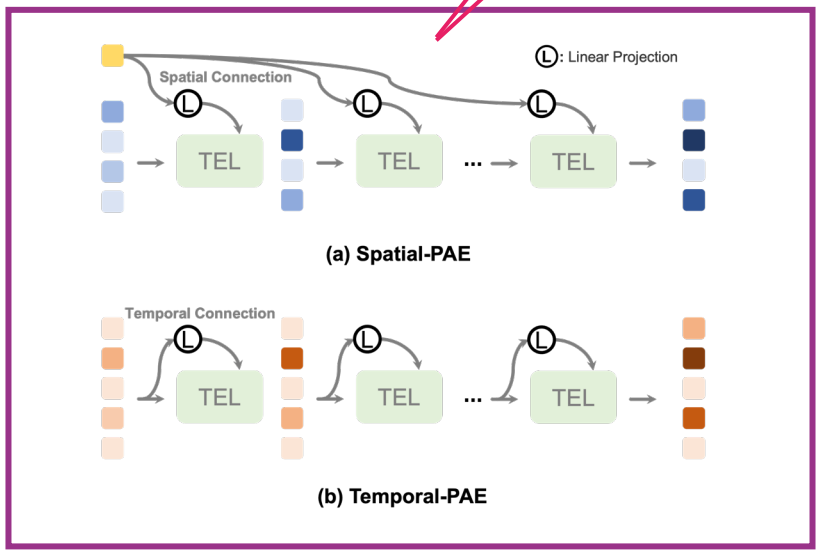
Slove

PIR utilizes a prior knowledge of remote sensing scene recognition to perform long–range dependency modeling for unbiased vision and text representations.

PIR Framework

- It contains Vision Instruction Representation (VIR), Language Cycle Attention (LCA) and Representation Alignment.
- Two PAE structures, Spatial–PAE and Temporal–PAE, are proposed to performs long–range dependency modeling.
- A cluster–wise attribution loss is proposed to constrain the inter–classes and reduce the semantic confusion zones in the common subspace.





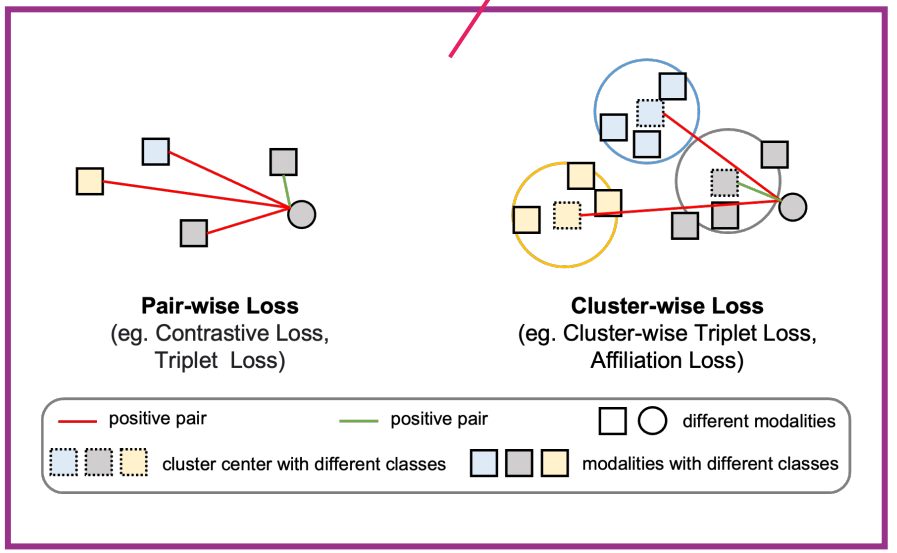


Table 1: Comparison results of the image-text retrieval on RSICD and RSITMD.

Method (Loss)	Backbone vision encoding / text encoding	RSICD Dataset Image-query-Text R@1 / R@5 / R@10	RSICD Dataset Text-query-Image R@1 / R@5 / R@10	RSICD mR	RSITMD Dataset Image-query-Text R@1 / R@5 / R@10	RSITMD Dataset Text-query-Image R@1 / R@5 / R@10	RSITMD mR
VSE_0 (TL)	ResNet-50 / GRU	4.56 / 16.73 / 22.94	4.37 / 15.37 / 25.35	14.89	9.07 / 21.61 / 31.78	7.73 / 27.80 / 41.00	23.17
SCAN i2t (TL)	RoI Transformer / GRU	4.82 / 13.66 / 21.99	3.93 / 15.20 / 25.53	14.19	8.92 / 22.12 / 33.78	7.43 / 25.71 / 39.03	22.83
SCAN t2i (TL)	RoI Transformer / GRU	4.79 / 16.19 / 24.86	3.82 / 15.70 / 28.28	15.61	7.01 / 20.58 / 30.90	7.06 / 26.49 / 42.21	22.37
CAMP (TL)	RoI Transformer / GRU	4.64 / 14.61 / 24.09	4.25 / 15.82 / 27.82	15.20	8.11 / 23.67 / 34.07	6.24 / 26.37 / 42.37	23.47
CAMERA (TL)	RoI Transformer / Bert	4.57 / 13.08 / 21.77	4.00 / 15.93 / 26.97	14.39	8.33 / 21.83 / 33.11	7.52 / 26.19 / 40.72	22.95
LW-MCR (TL)	CNN Blocks / CNN Blocks	3.29 / 12.52 / 19.93	4.66 / 17.51 / 30.02	14.66	10.18 / 28.98 / 39.82	7.79 / 30.18 / 49.78	27.79
AMFMN (TL)	ResNet-18 / GRU	5.21 / 14.72 / 21.57	4.08 / 17.00 / 30.60	15.53	10.63 / 24.78 / 41.81	11.51 / 34.69 / 54.87	29.72
GaLR (TL)	ResNet-18 + ppyolo / GRU	6.59 / 19.85 / 31.04	4.69 / 19.48 / 32.13	18.96	14.82 / 31.64 / 42.48	11.15 / 36.68 / 51.68	31.41
KCR (TL)	ResNet-101 / Bert	5.95 / 18.59 / 29.58	5.40 / 22.44 / 37.36	19.89	-	-	-
SWAN (TL)	ResNet-50 / GRU	7.41 / 20.13 / 30.86	5.56 / 22.26 / 37.41	20.61	13.35 / 32.15 / 46.90	11.24 / 40.40 / 60.60	34.11
VSE_1 (CL)	ViT / Bert	9.06 / 22.78 / 32.75	5.32 / 19.47 / 33.71	20.52	12.83 / 31.19 / 46.24	9.60 / 36.59 / 54.42	31.81
VSE_2 (TL)	Swin Transformer / Bert	7.96 / 21.68 / 34.31	6.44 / 22.09 / 37.49	21.66	17.70 / 36.28 / 48.67	**13.58** / 41.24 / 59.29	36.13
VSE_2 (CL)	Swin Transformer / Bert	**10.52** / 25.07 / 36.78	6.11 / 23.64 / 38.28	23.40	16.15 / 40.04 / **53.10**	10.75 / 38.98 / 60.18	36.53
VSE_2+TEL (CL)	Swin Transformer / Bert	10.43 / 25.89 / 37.15	6.02 / 23.42 / 38.30	23.53	17.48 / 36.95 / 50.44	11.81 / **41.99** / 61.77	36.74
PIR (CL+AL)	Swin Transformer + ResNet-50 / Bert	9.88 / **27.26** / **39.16**	**6.97** / **24.56** / **38.92**	**24.46**	**18.14** / **41.15** / 52.88	12.17 / 41.68 / **63.41**	**38.24**

The overall retrieval performance has an improvement of 4.0% on RSICD, and 4.1% on RSITMD

Pan et al., A Prior Instruction Representation Framework for Remote Sensing Image-text Retrieval, ACMMM 2023

Github: https://github.com/Zjut-MultimediaPlus/PIR-pytorch