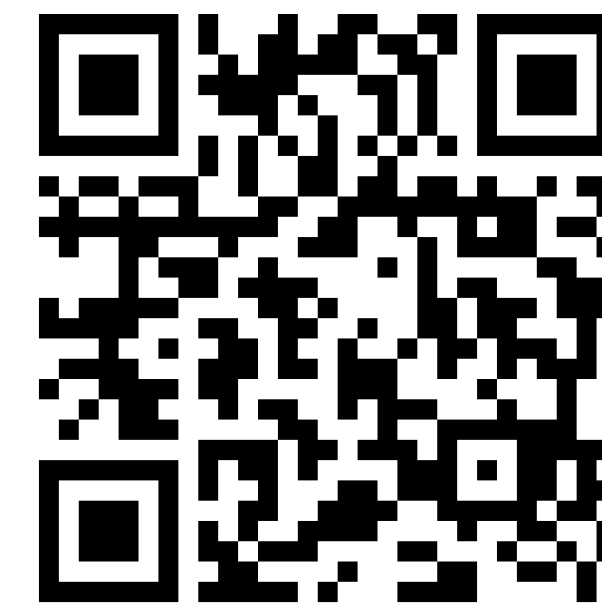# MARs: Multi-view Attention Regularizations for Patch-based Feature Recognition of Space Terrain

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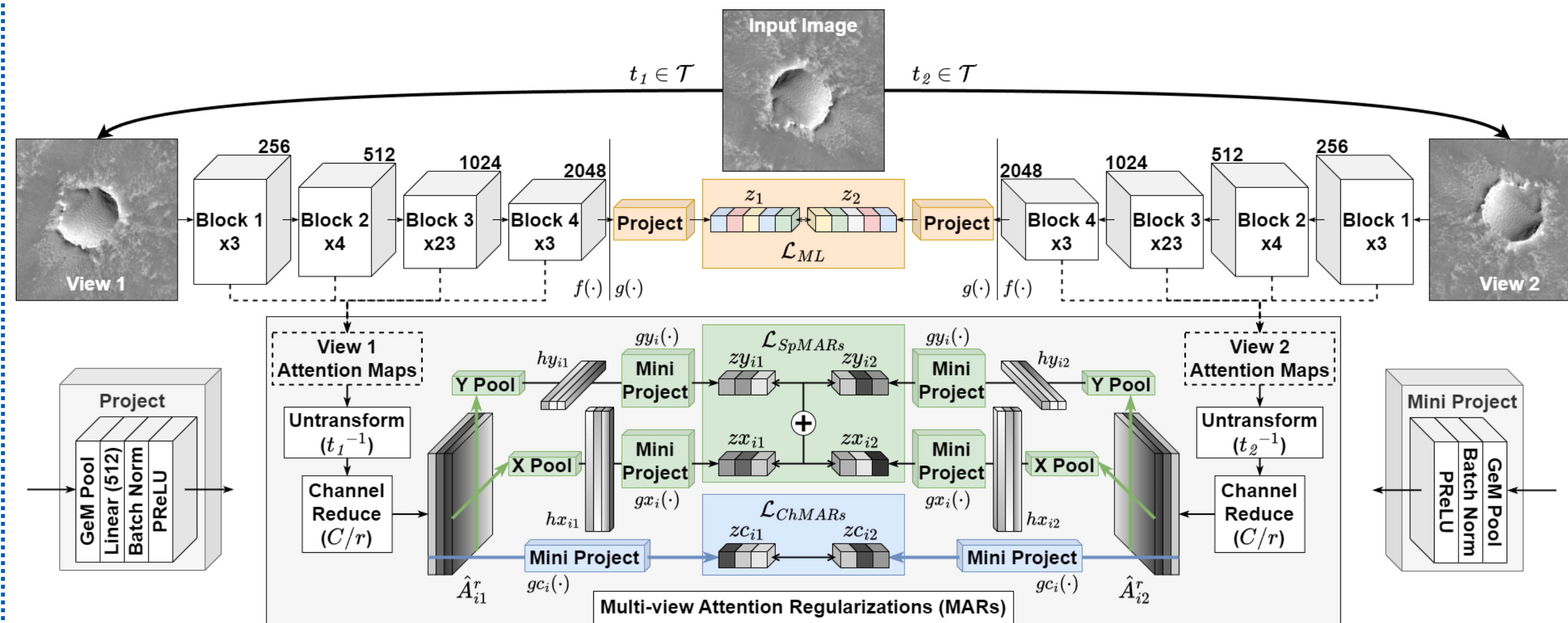
ECCV MILANO 2024

Motivation

Background: Spacecraft track pre-gathered, hand-crafted patch features (landmarks) with template matching for Terrain Relative Navigation (TRN).

Problem: Object detection-style methods are being deployed for increased autonomy; description still an open problem. **Metric learning unable to handle harsh appearance change in TRN**.

Traditional Attention
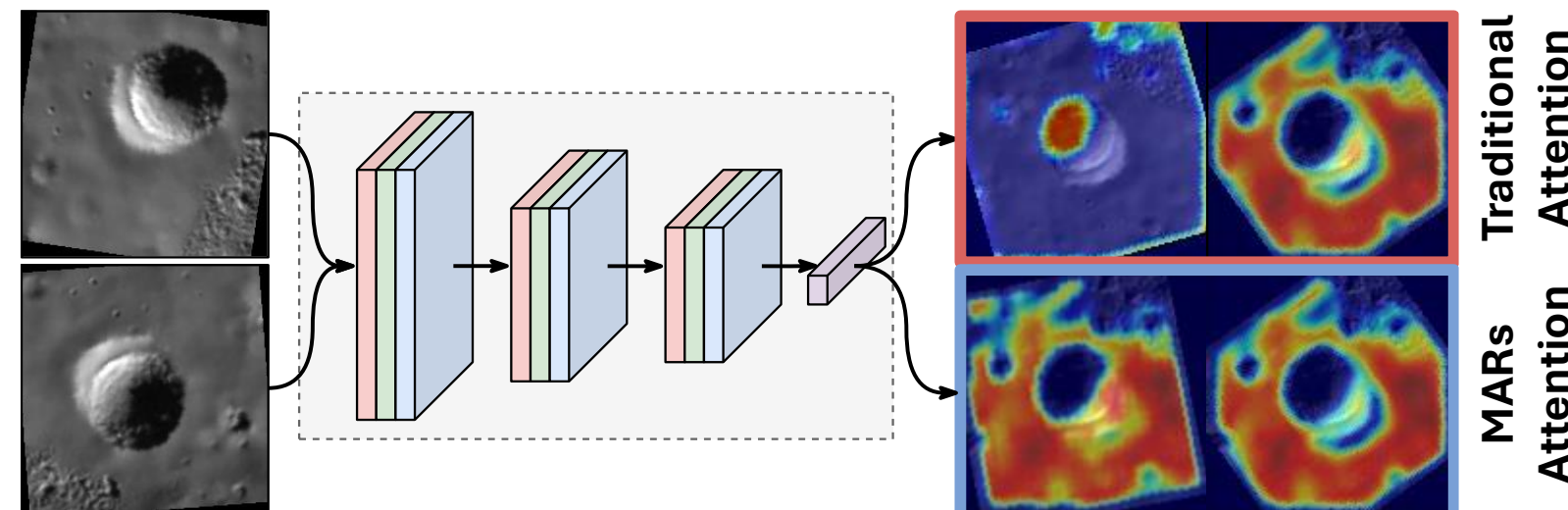
MARs Attention

Contribution: We propose soft-similarity constraints to make attention view-aware, increasing recognition on multi-view features.

Learning Multi-view Attention Similarity Constraints

Input Image

$t_1 \in \mathcal{T}$ $t_2 \in \mathcal{T}$

View 1 — 256, 512, 1024, 2048 — Block 1 x3, Block 2 x4, Block 3 x23, Block 4 x3 — Project — z_1 z_2 — $\mathcal{L}_{ML}$ — Project — Block 4 x3, Block 3 x23, Block 2 x4, Block 1 x3 — 2048, 1024, 512, 256 — View 2

$f(\cdot)$ $g(\cdot)$ $g(\cdot)$ $f(\cdot)$

View 1 Attention Maps — Project (GeM Pool, Linear (512), Batch Norm, PReLU)

hy_{i1} $gy_i(\cdot)$ Y Pool — Mini Project — $\mathcal{L}_{SpMARs}$ — zy_{i1} zy_{i2} — Mini Project — Y Pool — $gy_i(\cdot)$ hy_{i2} — View 2 Attention Maps

Untransform (t_1^{-1}) — X Pool — Mini Project — zx_{i1} zx_{i2} — $\oplus$ — Mini Project — X Pool — Untransform (t_2^{-1})

Channel Reduce (C/r) — $gx_i(\cdot)$ — $\mathcal{L}_{ChMARs}$ — $gx_i(\cdot)$ — Channel Reduce (C/r)

hx_{i1} — Mini Project — zc_{i1} zc_{i2} — Mini Project — hx_{i2}

$\hat{A}_{i1}^r$ $gc_i(\cdot)$ — Multi-view Attention Regularizations (MARs) — $gc_i(\cdot)$ $\hat{A}_{i2}^r$

Mini Project (Project, Batch Norm, PReLU, GeM Pool)

Improved Training

Attention learning with MARs (bottom pair) evolves similarly over time, **increasing training stability…**
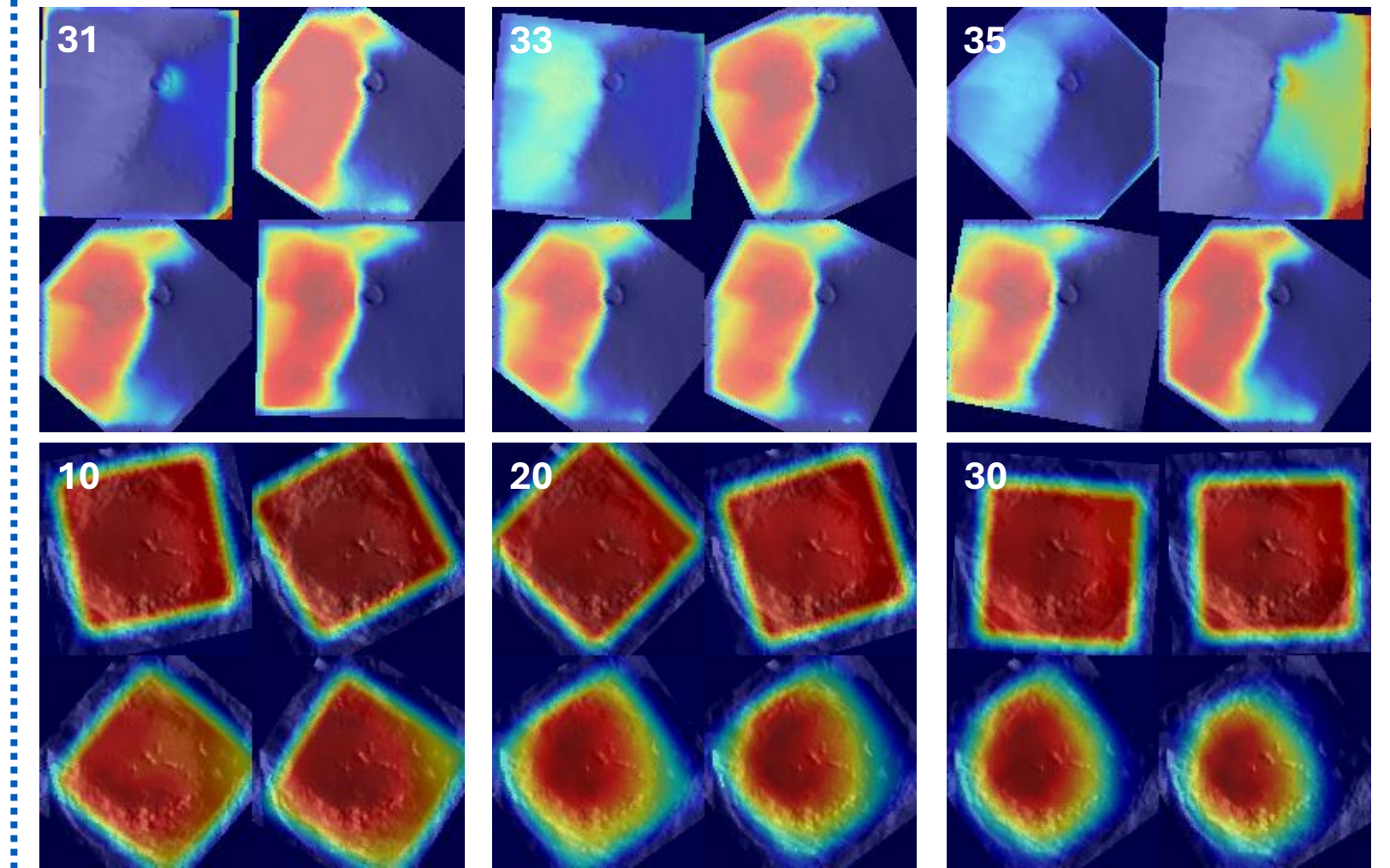
… and promotes **faster, more uniform convergence** compared with RIC CA (top pair).

Luna-1: A New Dataset

5,067 **Moon Crater** landmarks coupled with 2,161 **emulated navigation frames** derived from real-world NASA data for TRN research.
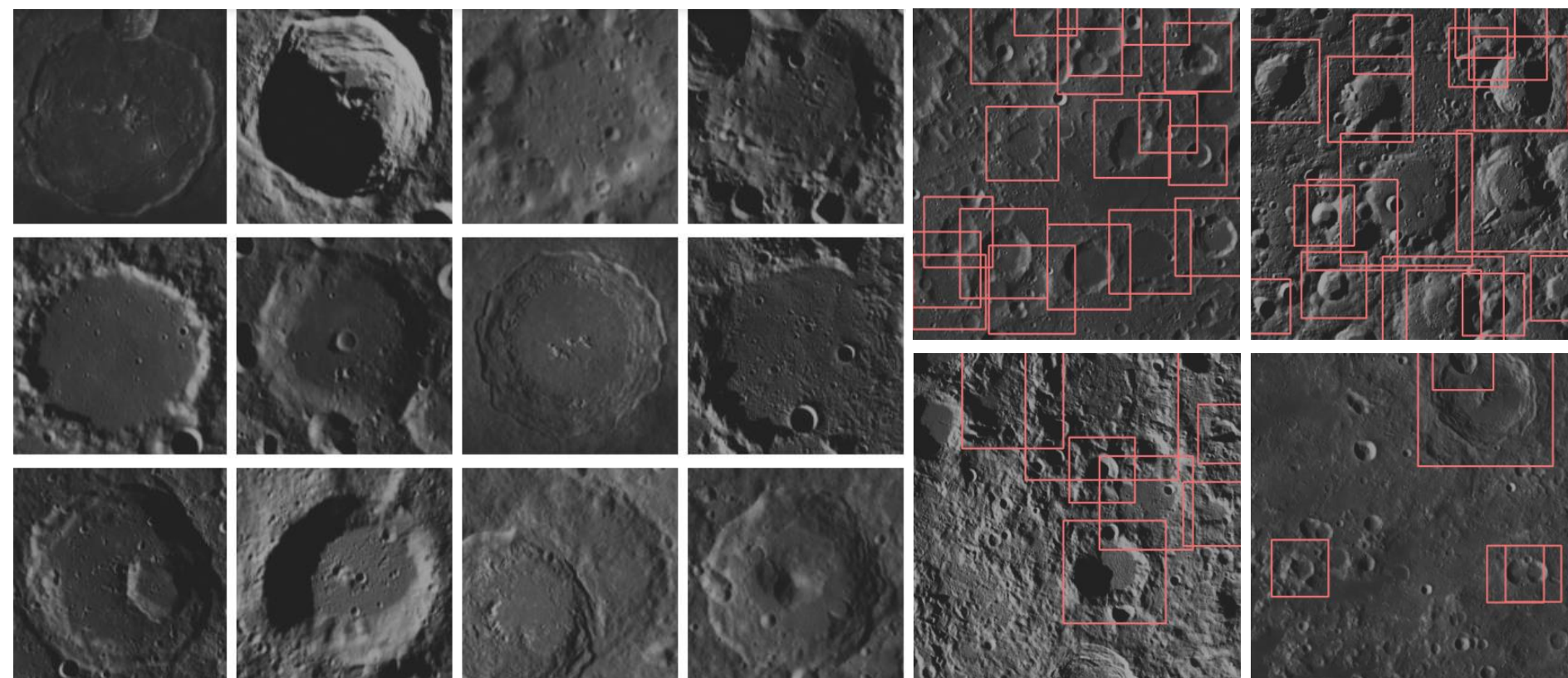
Boosting Landmark Recognition Performance

conv2d SE: *conv2d* and Squeeze-Excitation (channel only) attention.
RIC CA: Rotation-invariant convolution and Coordinate (channel and spatial) Attention.
MARs: *RIC CA* with *MARs* multi-view attention alignment.

$\mathcal{L}_{ML}$	Incremental Recall@1														
	Earth Stadium			Mars Crater			Moon Crater				Moon Navigation			Moon Lost-in-Space		
	conv2d SE	RIC CA	MARs (Ours)	conv2d SE	RIC CA	MARs (Ours)	conv2d SE	RIC CA	MARs (Ours)		conv2d SE	RIC CA	MARs (Ours)	conv2d SE	RIC CA	MARs (Ours)
Circle	4.79	5.11	**5.13**	3.59	**60.81**	12.56	43.36	**60.09**	30.46		58.07	37.97	38.46	94.03	**96.68**	92.31
DR-MS	4.33	5.27	**54.32**	4.04	**48.48**	4.04	62.55	2.47	**64.57**		**37.69**	3.12	36.68	86.34	88.06	**90.05**
NTXent	**12.23**	7.75	8.59	4.49	**34.10**	34.01	69.85	77.06	**81.69**		48.25	32.00	**57.68**	94.83	83.16	**96.29**
PNP	4.64	**5.27**	4.66	3.14	**16.70**	5.14	10.24	15.54	**40.84**		14.34	23.34	**24.66**	61.41	**77.98**	75.46
Proxy Anchor	4.48	72.86	**78.06**	3.44	10.45	**71.10**	94.56	–	**94.78**		64.17	–	**66.31**	**97.21**		96.02
ProxyNCA++	4.33	4.64	**12.00**	4.04	**7.71**	4.79	56.03	**71.23**	70.27		**58.27**	53.92	35.87	**94.69**	93.24	91.38
Subcenter ArcFace	**4.49**	4.48	4.19	3.29	4.99	**38.69**		–	**20.45**			–	**40.63**			**81.17**
SupCon	4.19	5.80	**46.43**	4.65	**57.52**	49.19	16.73	79.42	**84.11**		17.92	**42.28**	37.50	89.39	90.32	**90.58**
Proxy Synthesis	4.33	**39.41**	22.57	4.03	4.97	**35.14**	**91.40**	64.71	17.47		**61.26**	60.53	32.67	**96.42**	93.77	36.87

MARs **raises recognition accuracy** for many metric learning losses on navigation-style multi-view description with challenging appearance change and leads to **new state-of-the-arts** across environments.

Visual Alignment

RIC CA

MARs