The Fifteenth International Conference on Advanced Geographic Information Systems, Applications, and Services

Graph Neural Network for Accurate and Low-complexity SAR ATR

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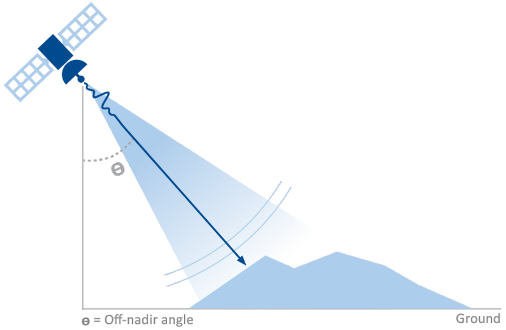
SAR Automatic Target Recognition (SAR ATR)

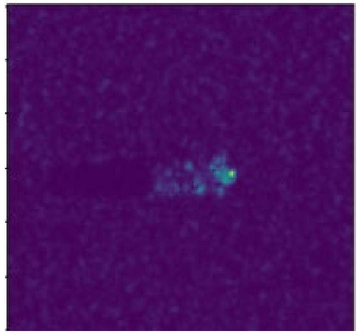
- SAR: Synthetic Aperture Radar
- SAR ATR: One of the most crucial and challenging issues in SAR application technology
- SAR image is captured by satellites or airplanes

Graph Neural Network for Accurate and Low-complexity SAR ATR



Satellite or Airplane

→

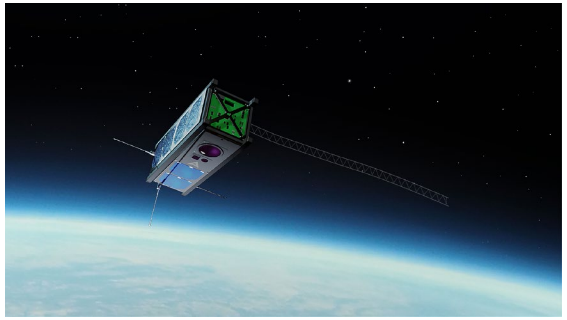


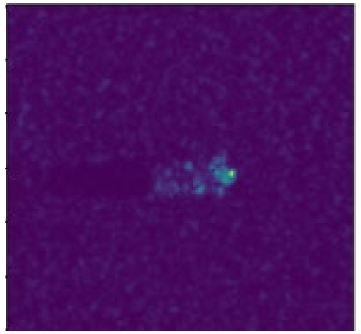
SAR image

→ SAR ATR system → Classification result

Challenges

- Traditional deep learning-based methods exploit convolutional neural network (CNN) for SAR ATR.
- CNNs have heavy convolution operations, leading to:
  - High computation complexity
  - Large memory requirement
- Due to the above challenges, SAR ATR is hard to be deployed on resource-limited platforms, such as small/micro satellites.
- CNN does not exploit the sparsity of the SAR image

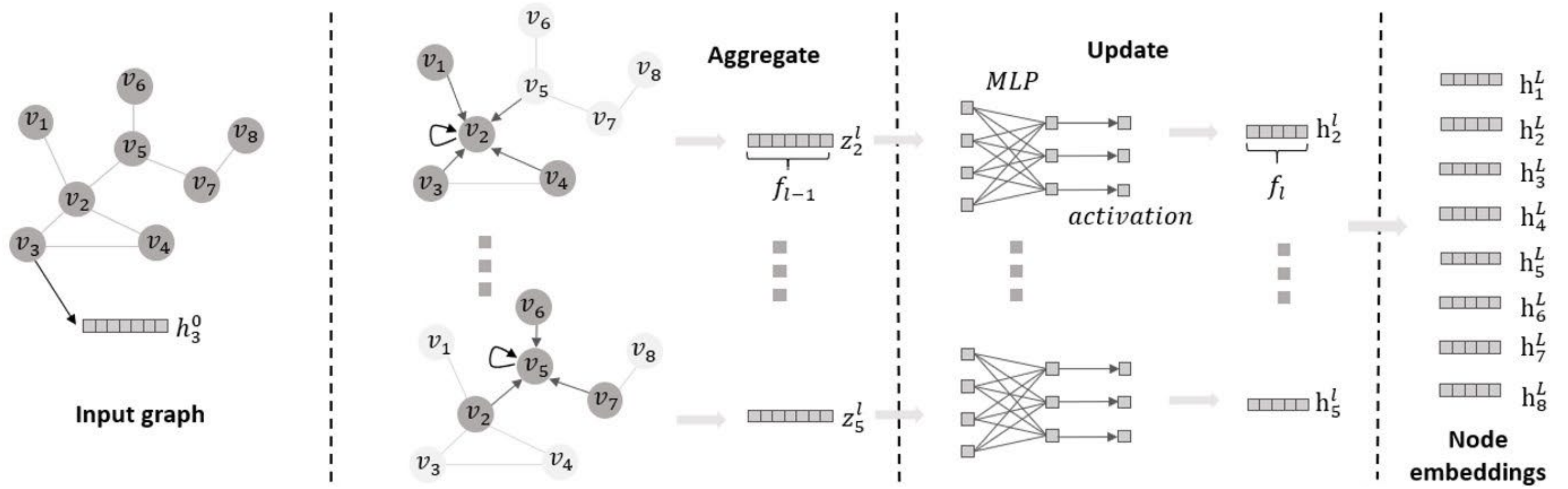




SAR image

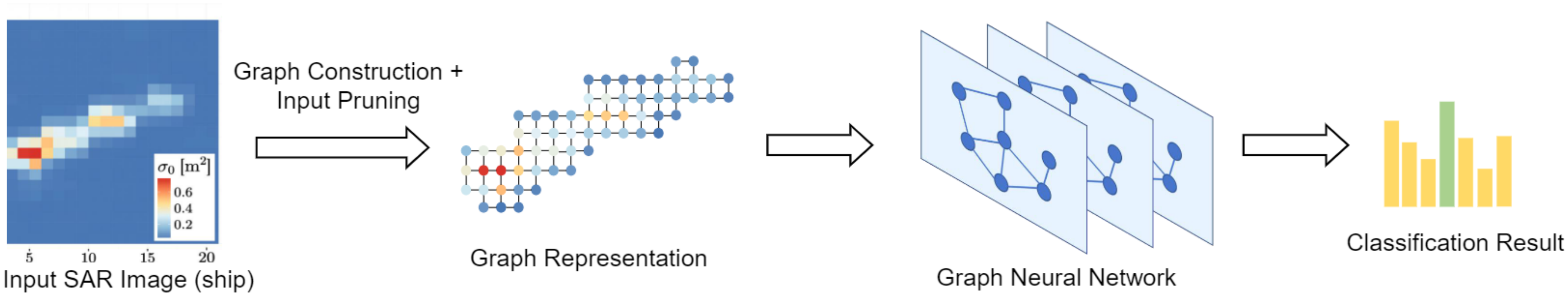
Graph Neural Network

- Graph neural network (GNN) has a stack of GNN layers. Each layer follows the Aggregate-update paradigm:
  - Aggregate: each vertex aggregates features from its neighbors
  - Update: each vertex feature vector is transformed by MLP



Motivation

- **Motivation 1:** Graph Neural Networks are powerful for graph classification
- **Motivation 2:** In a SAR image, most pixels are irrelevant
- **Proposed Approach**:
  - GNN-based model-architecture codesign
  - Construct input graph from SAR image
  - Develop a GNN model for classifying the graph



Proposed Approach

- Build input graph from SAR image:
  - $\mathcal{G}(\mathcal{V}, \mathcal{E}, X)$
  - Each pixel in the SAR image is mapped to a vertex $v \in \mathcal{V}$ in the graph
  - Each pixel is connected to its neighbors as the edge connections $\mathcal{E}$.
    - 4-connectivity
    - 8-connectivity

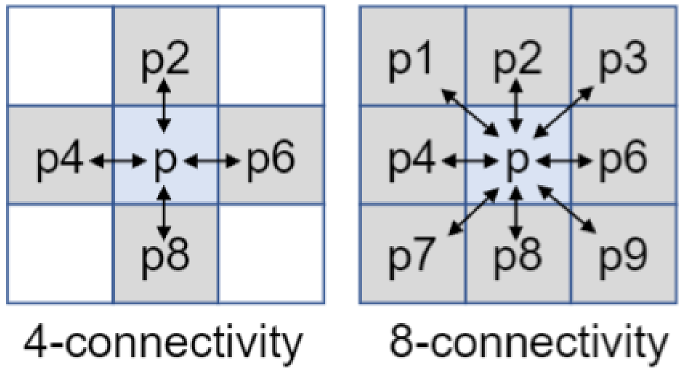


Figure 4. Two types of connectivity for constructing input graph

Proposed Approach

- Model Architecture
  - Graph Neural Network layer
    - E.g., GCN, GraphSAGE, GIN, SGC, etc
  - Graph pooling layer
  - Attention layer
    - Feature Attention: identify important vertex features
    - Vertex Attention: identify important vertices

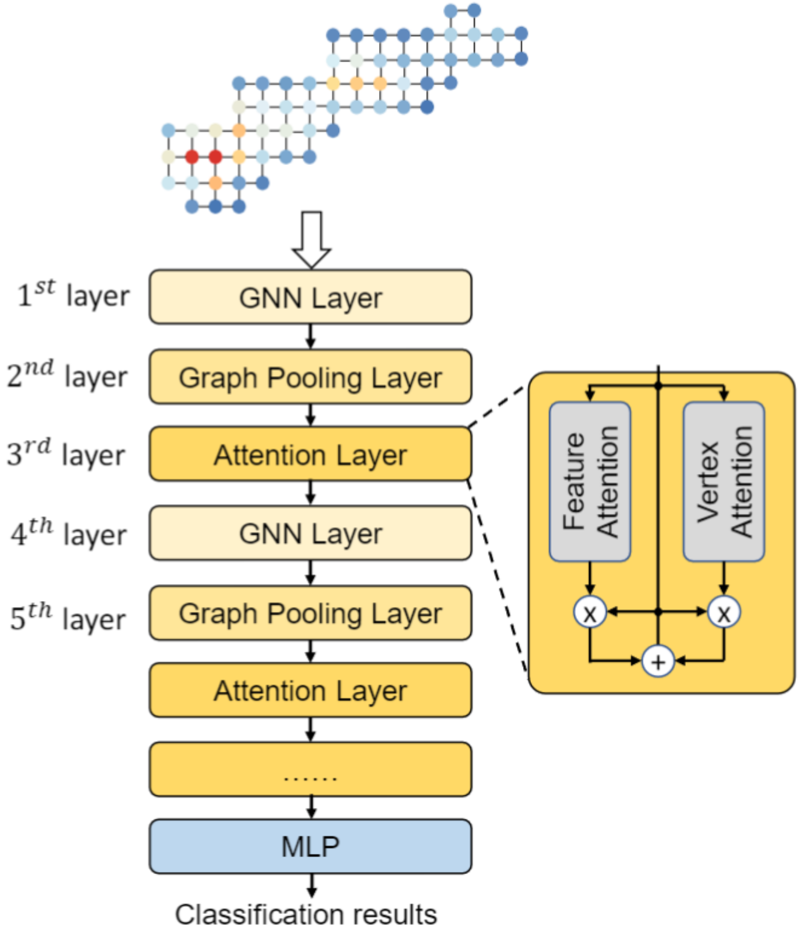
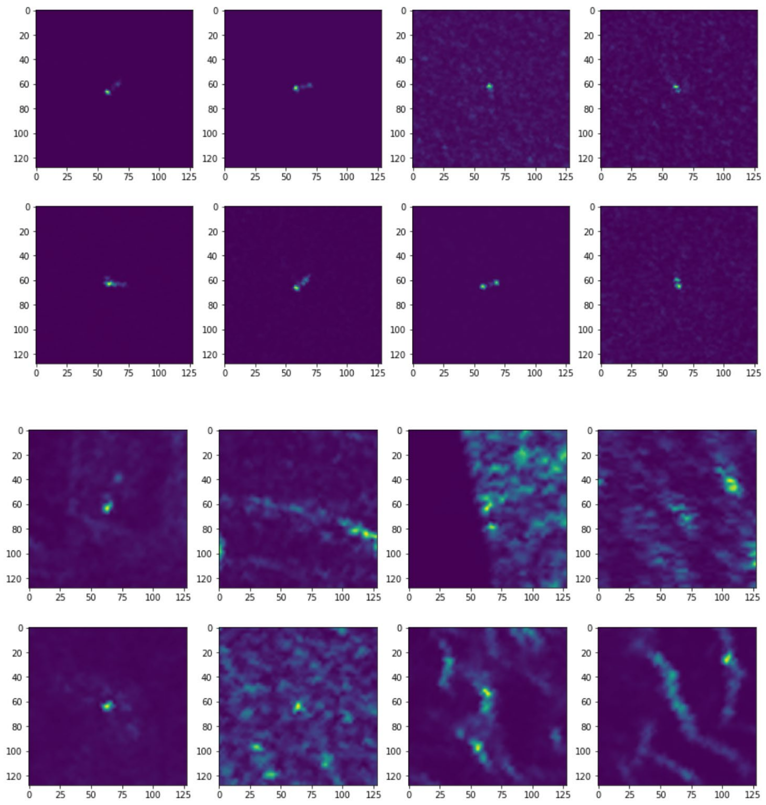


Figure 5. Diagram of model architecture

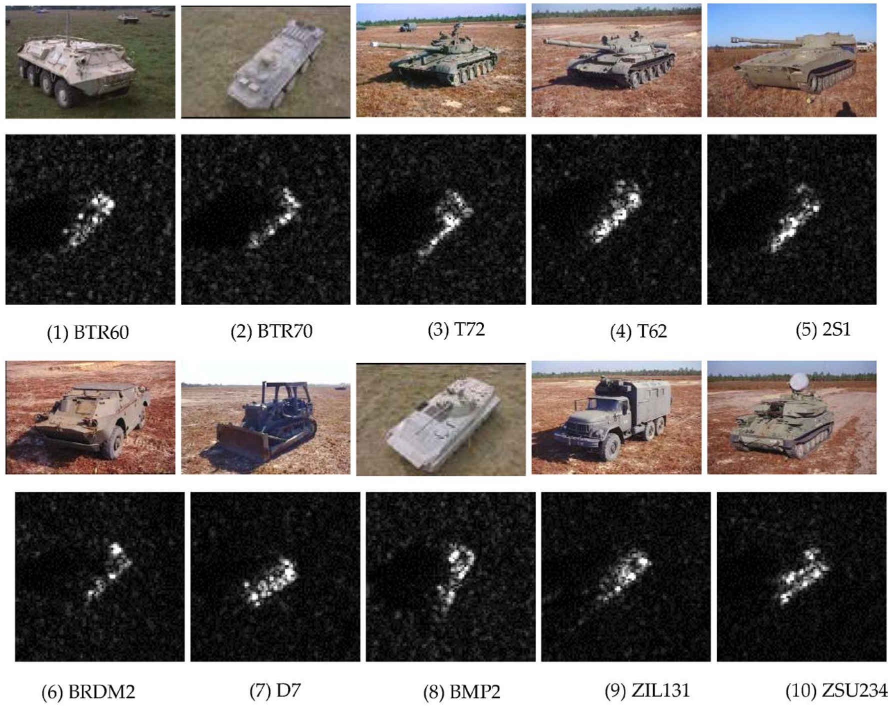
Dataset

- Moving and Stationary Target Acquisition and Recognition (**MSTAR**) dataset
- Ship discrimination dataset

Ship discrimination dataset



MSTAR dataset



Experimental Result (MSATR dataset)

- Impact of GNN backbone:
  - GraphSAGE layer leads to highest accuracy

TABLE II. THE ACCURACY ON MSTAR DATASET

GNN Layer Type	Connectivity	Training Accuracy	Testing Accuracy	Training Time
GCN	4	99.16%	90.06%	3.0 hours
	8	95.44%	83.82%	4.0 hours
GAT	4	99.53%	92.21%	1.8 hours
	8	82.71%	71.33%	1.9 hours
GraphSAGE	4	100.00%	97.81%	52 min
	8	100.00%	99.38%	55 min

- Impact of attention mechanism:
  - Both vertex attention and feature attention lead to increased accuracy

TABLE IV. THE IMPACT OF THE ATTENTION MECHANISM (USING GRAPHSAGE LAYER AND 8-CONNECTIVITY)

Vertex Attention	Feature Attention	Training Accuracy	Testing Accuracy	Training Time
✗	✗	99.67%	93.77%	31 min
✗	✓	100.0%	98.51%	40 min
✓	✗	100.0%	99.26%	41 min
✓	✓	100.0%	99.38%	55 min

Experimental Result (MSATR dataset)

- Comparison with state-of-the-art:
  - The proposed GNN model achieves higher accuracy compared with the state-of-the-art CNNs [11], [12], [14], [15] with negligible computation complexity for inference.

TABLE III. COMPARISON WITH THE STATE-OF-THE-ART CNNS ON MSTAR DATASET

	Type	Accuracy	# of FLOPs	# of Para.
[11]	CNN	92.3%	$\frac{1}{12}\times$	0.5×10^6
[14]	CNN	97.97%	$\frac{1}{10}\times$	0.65×10^6
[15]	CNN	98.52%	$\frac{1}{3}\times$	2.1×10^6
[12]	CNN	99.3%	$1\times$ (6.94 GFLOPs)	2.5×10^6
This work [after pruning] (GraphSAGE layer, 8-connectivity)	GNN	99.1%	$\frac{1}{3000}\times$	0.03×10^6

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- [15] Z. Ying, C. Xuan et al., “Tai-sarnet: Deep transferred atrous-inception cnn for small samples sar atr,” Sensors, vol. 20, no. 6, p. 1724, 2020

Acknowledgement & Contact Info.

- This work was supported by
  - NSF: CCF-1919289, OAC-2209563
  - DEVCOM Army Research Lab (ARL) under grant:
    - W911NF2220159.

- If you have any questions, please contact us through the email bingyizh@usc.edu
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