SIGNN – Star Identification using Graph Neural Networks

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Abstract

Abstract: As a solution for the lost-in-space star identification problem we present Star Identification using Graph Neural Network (SIGNN), a novel approach using Graph Attention Networks. By representing the celestial sphere as a graph data structure, created from the ESA's Hipparcos catalogue, we are able to accurately capture the rich information and relationships within local star fields. Graph learning techniques allow our model to aggregate information and learn the relative importance of the nodes and structure within each stars local neighbourhood to it's identification. This approach, combined with our parametric data-generation and noise simulation, allows us to train a highly robust model capable of accurate star identification even under intensive noise, outperforming existing methods.

Introduction

Motivation:

- Celestial navigation as an offline alternative to GPS, which is vulnerable to interference (spoofing, jamming, outages etc).
- Star detection is largely solved, but *star recognition* remains challenging in noisy conditions
- Graph Neural Networks (GNNs) can capture complex relationships in graph data

Contribution:

- **SIGNN** uses graph-based representations of star-fields + noise simulations to learn robust star representations for identification.
- Achieves superior accuracy over classical and ML-based methods, even at high noise.

Existing Work & Celestial Sphere

Classical:

- **Sub-graph isomorphism** (Triangle, pyramid)
- **Star pattern recognition** (Grid, radial)

Machine Learning:

- **CNN-based**: spider-web images.
- **Representation learning**: RPNet w/ autoencoders

Celestial Sphere (RA/DEC):

- Stars mapped via **Right Ascension (RA)** and **Declination (DEC)** analogous to longitude/latitude on Earth
- **Celestial coordinates** used to compute angular separations (**edges**) among connected stars in a **graph representation** that preserves exact **geometry** and **precision**.

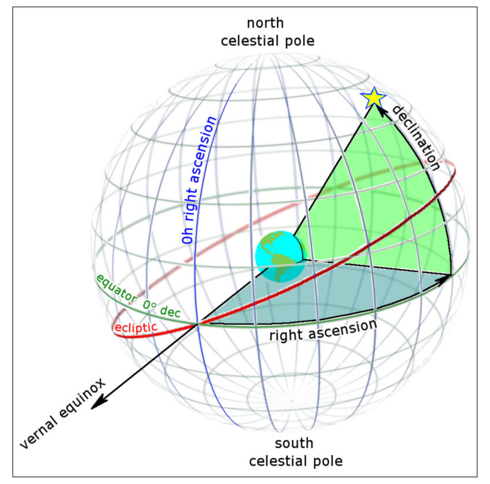


Figure: Visualization of RA/DEC on the celestial sphere.

Methodology – Graph Construction

Celestial Sphere Graph Nodes & Edges:

- Star data extracted from Hipparcos catalogue
- Nodes = stars (RA, DEC, V_{mag}).
- Edges = angular distance (Vincenty) < τ (3°).

Filtering:

- Exclude stars fainter than magnitude 6.0 (visible to naked eye / simulated sensor threshold).
- Remove isolated nodes (fewer than 2 neighbours).

Source Detection:

- In real images, detect centroids → convert to angular measures.
- Accurate absolute V_{mag} is challenging; use relative brightness among direct neighbours (min-max).

Resulting Input Graph:

- Each node's feature = local relative magnitude (brightness compared to direct neighbours).
- Edges represent angular distance, min-max scaled.
- Pattern radius = 3°; 2-hop coverage = 6°.
- Final graph size: 4274 nodes, 20K edges.

Methodology – SIGNN Architecture

SIGNN Pipeline:

- **2 GAT layers** → linear classifier
- **Multi-noise** training: positional, dropped, false, magnitude
- **Nodes aggregate** from neighbours' features and edge features (angular distances)
- 2-hop receptive field of 6°

GAT (2-layer):

$$\mathbf{x}'_i = \Vert_{h=1}^{H} \, \sigma \left(\sum_{j \in \mathcal{N}(i) \cup \{i\}} \alpha_{i,j}^{h} \, \mathbf{W}^{h} \mathbf{x}_j \right)$$

where $\alpha_{i,j}^{h}$ are learnable attention coefficients.

Attention Mechanism:

- Each node attends to its neighbours
- Learnable weights ($\alpha_{i,j}^{h}$) focus on important and reliable connections

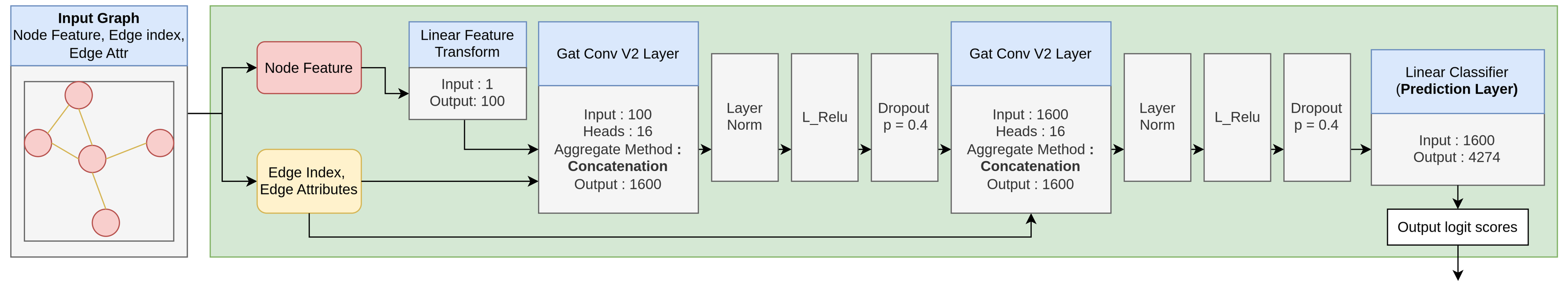
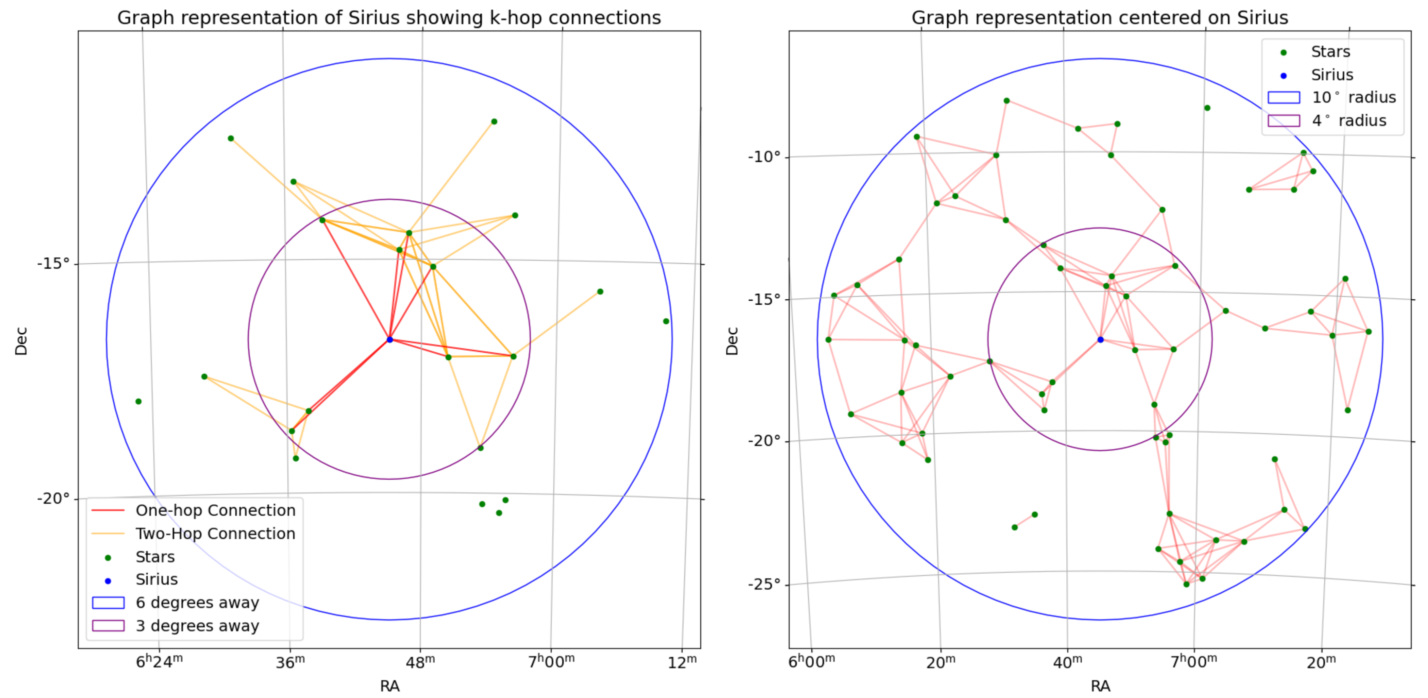


Figure: SIGNN architecture

Example: Sirius neighbourhood

Sirius (2-Hop neighbourhood):

Sirius is connected to its neighbours within 3°, then those neighbours connect further within 3°. The GAT layers aggregate these relationships to correctly identify Sirius despite noise. Below, we show two perspectives: (a) the immediate 2-hop neighbourhood, and (b) a 10° FOV subgraph centred on Sirius, showing an example sensor input.



(a) 2-Hop around Sirius, only connected nodes are used in the representation of Sirius (b) 10° FOV subgraph, simulated sensor input

Figure 1. Two visual perspectives of Sirius: a closer 2-hop neighbourhood vs. a wider 10° view.

Real World vs Noise Simulation

Noise Types:

- **Positional:** shift star RA/DEC by random angular distance offsets
- **Dropped:** randomly remove stars (cloud, occlusion)
- **False:** insert false sources (aircraft, sensor noise)
- **Magnitude:** perturb brightness by random %

Sensor Issue	Detection Output	Noise Simulation
Weather	Missing stars	Drop
	Wrong mag	Mag noise
Occlusion	Missing stars	Drop
Atmospheric Effects	Shift position	Position noise
	Vary mag	Mag noise
Lens distortion	Shift position	Position noise
Lights	Extra stars	False

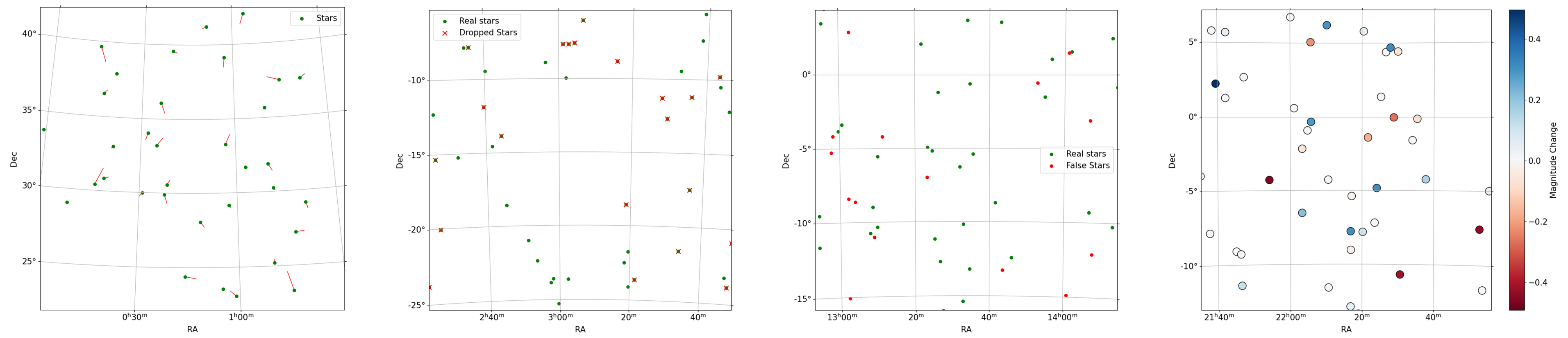
Noise Simulation & Training

Training Details:

- 500 epochs, batch size = 64
- Each epoch: 1024 variations of entire celestial sphere (20% each noise + 20% no noise)
- **Parametric dataloader** generates noisy samples during training. Fast.
- No need for large, static stored dataset
- Bayesian optimization for hyperparams
- Each star predicted on ≈ 480k times during training

Noise Type	Start	End	Step
Position (Std Dev Radians)	0.0001	0.001	0.0001
Magnitude (%)	1%	10%	1%
False (%)	5%	50%	5%
Dropped (%)	5%	50%	5%

Table 2. Testing schema for noisy star recognition.



(a) Positional Noise (b) Dropped Star Noise (c) False Star Noise (d) Magnitude Noise

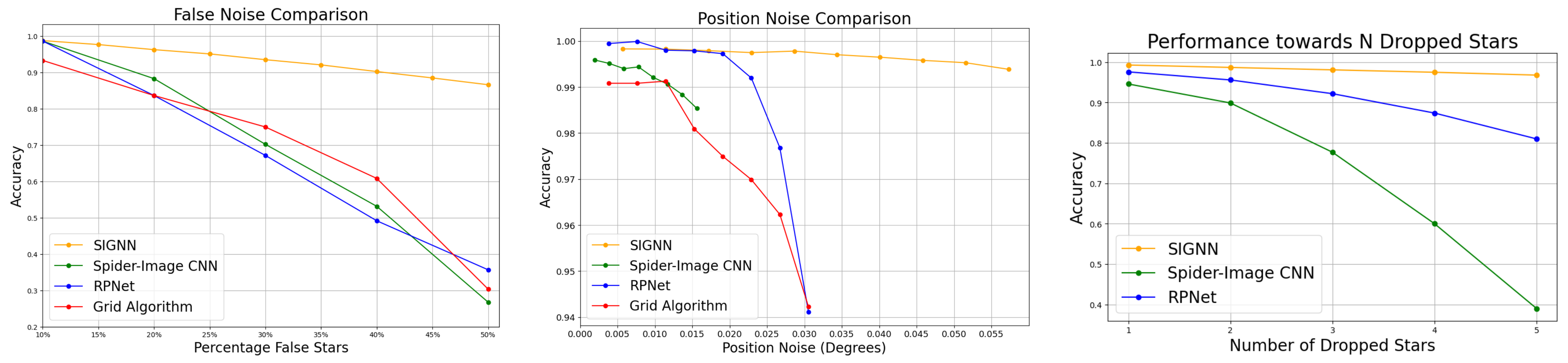
Figure 2. Four main noise types visualized.

Results & Noise Performance

Test Setup:

- Generate random FOV-subgraphs (10°) across the celestial sphere, simulating sensor views with random boresight and location.
- 20k images per noise type and level : 800k images, 28 million star predictions.

Comparisons: Classical (Grid), ML (RPNet, Spider).



(a) False noise (b) Positional noise (c) Dropped noise

Figure 3. SIGNN outperforms prior methods under high noise.

Discussion & Future Work

Insights:

- SIGNN yields high accuracy for star in FOV under considerable noise conditions
- Graph representation and angular-distance approach is *sensor-agnostic*.

Future:

- **Edge-of-image** problem: partial star patterns near FOV boundary.
- Extend to variable and fainter magnitude thresholds.
- Creation of real image dataset + testing

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