Exoplanet Detection from Starshade Images using Convolutional Neural Networks

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To fully harness the potential of direct imaging for exoplanet detection, there is a need for image processing algorithms that address 3 main challenges:

1. **Efficiency & Scalability** — Data management for petabytes of direct imaging data
2. **Versatility** — Design validation for diverse mission architectures, including starshades
3. **Accuracy** — Detection from low signal-to-noise images

**CONVENTIONAL APPROACHES**

Conventional image processing algorithms have primarily been tailored to coronagraph images and often rely on visual inspection to make accurate detections. Specific techniques include:

- **Spectral Differential Imaging (SDI):** An observing technique that captures sequences of images across multiple wavelengths and can be paired with post-processing algorithms
- **Independent Component Analysis (ICA):** A statistical technique for decomposing multivariate signals, which can be used to estimate and remove background noise

**REFERENCES**

1. Astro2020 Decadal Survey
2. Ronneberger et al. 2015
3. Lin et al. 2018
4. Hildebrandt et al. 2021
5. Wang et al. 2015
6. Hu et al. 2021
7. Dunne 2022

**NEW APPROACH**

**Convolutional Neural Networks (CNN)**

CNNs are an efficient and versatile alternative to state-of-the-art image processing algorithms but have had limited application to direct imaging due to lack of training data.

**Modified U-Net Architecture and Training Pipeline**

3 main modifications:

1. Network Depth
2. 3-channel Detection Head
3. Mean-squared error and focal loss

**Synthetic Starshade Dataset**

The dataset was generated using the Starshade Exoplanet Simulation Toolkit for Exoplanet Reconnaissance (SISTER) and consists of 1,440 broadband images.

**RESULTS**

![Figure 4: Training and validation loss converged consistently and show good agreement, indicating that the model did not overfit despite limited training data.](image)

**Table 1: CNN performance versus SDI and ICA pipelines.**

<table>
<thead>
<tr>
<th>Method</th>
<th>Precision</th>
<th>Recall</th>
<th>L2 Error [μJ]</th>
</tr>
</thead>
<tbody>
<tr>
<td>SDI</td>
<td>0.197</td>
<td>0.223</td>
<td>1.88</td>
</tr>
<tr>
<td>ICA</td>
<td>0.600</td>
<td>0.490</td>
<td>1.057</td>
</tr>
<tr>
<td>CNN</td>
<td>0.925 ± 0.012</td>
<td>0.923 ± 0.018</td>
<td>0.584 ± 0.017</td>
</tr>
</tbody>
</table>

**FUTURE WORK**

1. Expand starshade dataset to increase robustness of CNN and improve ability to generalize.
2. Tailor CNN architecture to incorporate physics models of exoplanet signals

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![Image 1: (Left) Rendering of starshade-telescope system. Credit: NASA/JPL. (Right) Synthetic starshade image with two exoplanet signals (red boxes).](image)

![Image 2: CNN training (solid orange line) and inference (dashed blue line) pipelines.](image)

![Image 3: Sample SISTER images with varying levels of noise.](image)

![Image 5: Feature maps show how input is transformed through CNN.](image)

![Image 6: Sample CNN predictions (red circle) versus ground truth (blue square).](image)

![Table 1: CNN performance versus SDI and ICA pipelines.](table)

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![CNN achieves precision and recall > 0.9 and can perform inference on single images without the need for background subtraction.](image)