Deep neural network for high-contrast imaging

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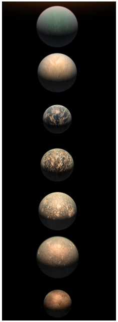
Introduction
Motivation for HCI

Exoplanets detection via High Contrast Imaging (HCI)

- Most of current identified exoplanets detected via **indirect techniques**
- Indirect techniques very effective within the first AU
- HCI allowing detections for **larger separation** for both "face-on" and "edge-on" systems
- Spectroscopy and HCI giving deeper insights into **exoplanets characteristics**

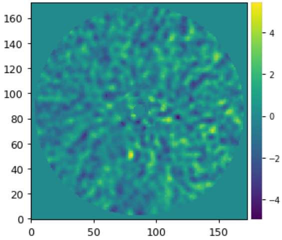


Credits: Nasa

Introduction
HCI Main pillars

HCI five pillars

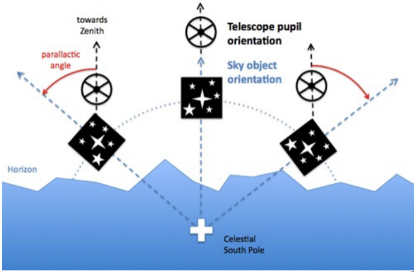
- Large telescopes ⇒ **Resolution**
- Advanced adaptive optics systems ⇒ **Resolution**
- Coronographs ⇒ **Contrast**
- Observing strategies ⇒ **Speckles**
- Post processing techniques ⇒ **Speckles + Contrast**



ER51 APCA SNR map

State of the art
Observing Strategy

Angular Differential Imaging (Marois, 2006) representing the main observing strategy for HCI



Somboonpanyakul and Tamura, 2014

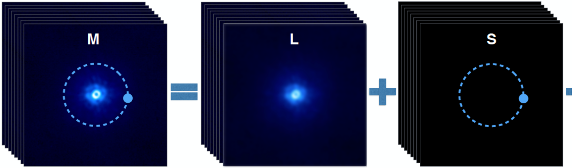
- Set of images taken in **pupil tracking mode**
- Instrument **centred** on given star
- Potential exoplanets **rotating** while stellar diffraction pattern remains **fixed**
- Most of **quasi-static speckles** removed by subtracting the **median** from each frame

State of the art

HCI post-processing techniques

Most recent HCI post-processing techniques relying on **low rank approximation** (PCA/KLIP, Annular PCA, NMF, LLSG)

⇒ **Creation** and **subtraction** of **noise map** to retrieve the planetary signal



Gomez Gonzalez et al., 2016

State of the art

HCI post-processing techniques

Procedure steps:

- Estimation of a **reference point spread function** regrouping the instrument noise and star light via low rank approximation
- **Subtraction** of the reference point spread function from the set of images
- **Alignment** of the resulting set of residual images
- Estimation of final frame by **mean-combining** the set of aligned images
- Planetary candidates selection via **signal to noise ratio** thresholding

State of the art

Machine learning based post-processing technique

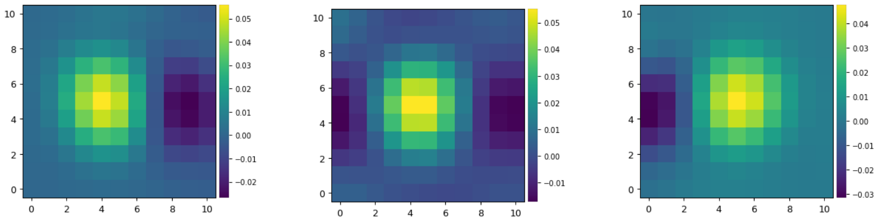
Reformulating the exoplanet detection task as a supervised binary classification problem (Gomez Gonzalez et al. (2018))

- Estimation of Multi-level Low-rank Approximation Residual (MLAR)
  - Estimation of a **reference point spread function** for several low rank values
  - **Subtraction** of the reference point spread function from the set of images
  - **Alignment** of the resulting set of residual images
  - **Mean-combining** along the temporal axis
  - Patches creation via **cropping** (3D cubes centered on every pixels of the frame)
- Deep neural network to **classify** the resulting patches

Model
Time dependent model

Project main objectives:

- **Adapt** the approach of Gomez Gonzales et al. to take into account the **time structure** of the ADI sequence
- Test **other architectures** of deep neural network
- Use **ROC curves** to compare the performance of the algorithms



Model
Time dependent model

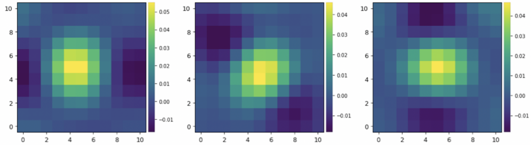
Take into account the time structure of the ADI sequence

- Estimation of Multi-level Low-rank Approximation Residual (MLAR)
  - Estimation of a **reference point spread function** for several low rank values
  - **Subtraction** of the reference point spread function from the set of images
  - **Alignment** of the resulting set of residual images
  - ~~**mean-combining** along the temporal axis~~
  - Patches creation via **cropping** (4D cubes centered on every pixels of the frame)
  - Estimation of moving averages to reduce the **noise level** and **size** of the 4D patches
- Deep neural network to **classify** the resulting patches

Model
Architecture

Deep neural network architecture based on:

- 2D convolutional LSTMs
- Maxpooling layers
- Dense layers



Input: 4D MLAR patches
(200,9,9,10)
↓
Moving average (20,5)
(35,9,9,10)
↓
2D Convolutional LSTM ((3,3),(2,2),30)
(35,4,4,30)
↓
MaxPooling ((1,2,2),(1,1,1))
(35,3,3,30)
↓
2D Convolutional LSTM ((2,2),(1,1),20)
(35,2,2,40)
↓
MaxPooling ((5,1,1),(5,1,1))
(7,2,2,40)
↓
Flatten
1120
↓
Dense Network (128 units)
1120
↓
Activation (ReLU)
128
↓
Dense Network (1 units)
1
↓
Activation (Sigmoid)
1

Model
Training and learning samples

Estimation of positive and negative classes done **annulus-wise**:

- Positive class C^+:
  - Positive MLAR patches obtained by **injecting fake companions**
  - Flux values for the **learning sample** $\rightarrow$ companions with a SNR between 3 and 5
  - Flux values for the **test sample** $\rightarrow$ companions with a SNR between 1 and 3
- Negative class C^-:
  - Exploit the rotation associated with ADI techniques $\rightarrow$ **flip the sign** of the parallactic angles
  - Sample **mixing**, **rotations** and **shifts** to create more samples

Results

Datasets

Selected pre-processed datasets:

- VLT NACO: Beta pictoris (ADI sequence containing 204 frames, integration time of 8 s, field rotation of 83 degrees)
- VLT SPHERE: ERI 51 (ADI sequence containing 197 frames, integration time of 4 s, field rotation of 49.3 degrees)

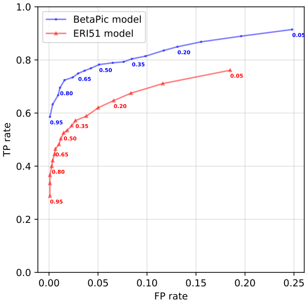
$\Rightarrow$ Optimal architecture selection based on **loss function value**

$\Rightarrow$ Datasets considered **separately** and **jointly**

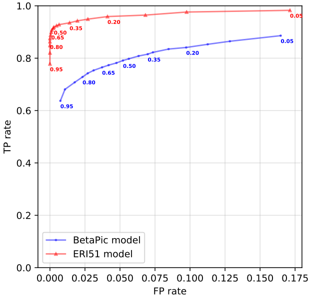
$\Rightarrow$ **Performance comparison** with the SODINN based on ROC curves

Results
ROC curves

ROC curve for separate models:



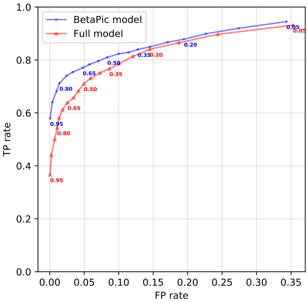
Beta Pictoris



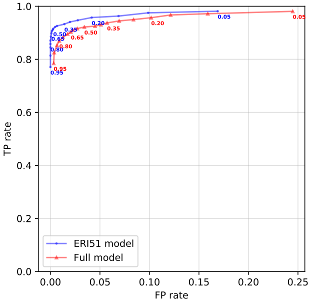
Eridani 51

Results
ROC curves

ROC curve for joint model:



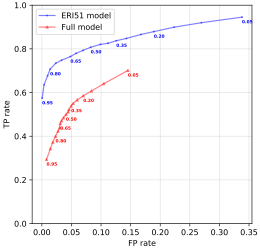
Beta Pictoris



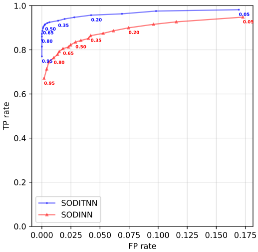
Eridani 51

Results
ROC curves

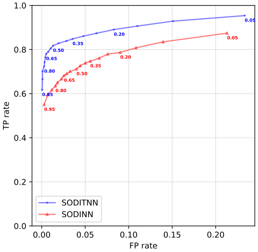
Comparison with SODINN:



Beta Pictoris



Eridani 51



Beta Pictoris + Eridani 51

Conclusion

Exoplanets detection via deep learning methods

- New deep neural network architecture using the **temporal structure** of ADI sequences
- **Several architectures** tested on ADI datasets
- Model parametrization using the **ERI 51** and **Beta Pictoris** datasets separately or jointly
- **Background noise structures** leading to differentiate models
- **Full model** providing results close to the **dedicated ones**
- All three considered models **performing better** than SODINN