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A Review of Post-Processing Algorithms in Direct Imaging of Exoplanets

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Abstract- *Direct imaging involves the use of coronagraphs to block the light from the star in order to observe exoplanetary systems. Various factors, such as image deterioration by turbulence in Earth's atmosphere, small angular separation between the planets and the star, as well as the high contrast ratio between them makes direct imaging a challenging method to detect exoplanets. Post-processing algorithms serve a quintessential role by reducing the background noise and hence, drastically improve detectability. With rapid progress being made in terms of imaging capabilities, such as the proposed introduction of the Wide-Field Infrared Survey Telescope (WFIRST), a comprehensive review of the algorithms and post-processing strategies would allow direct imaging to be adaptive to the progress and consequently, improve the rate of detection. In this study, the critical analysis of three algorithms – the non-principal component analysis (non-PCA) based LOCI algorithm [10]; the PCA based PynPoint [2]; and the robust PCA based LLSG algorithm [9] is conducted. Furthermore, the effectiveness of these algorithms is discussed in various imaging conditions. Prospects of the interrelation of computer vision and astronomy are briefly discussed.*

Keywords: direct imaging; image processing; exoplanet detection; computer vision algorithms

I. INTRODUCTION

The launch of NASA's Kepler space telescope has led to an unprecedented rate of discovery of exoplanets. Although more than 3,600 exoplanets were discovered as of July, 2017, only about 850 of those detections utilized direct imaging [22]. This low rate is attributed to various obstacles – both in imaging and processing stages. This includes the high luminosity contrast between the host star and the exoplanet; background noise due to the turbulence in Earth's atmosphere; subpar quality of the coronagraph as well as the requirement of high quality optical instruments [9]. Currently, planets in their primitive stages of evolution are easier to detect, due to their comparatively higher temperatures. Furthermore, the size of the planets detected using this method is usually larger than Jupiter [12]. However, the imaging capabilities of telescopes are drastically improving and missions such as WFIRST are being developed specifically for direct imaging for exoplanets [3]. As a consequence, it is imperative to develop effective algorithms that could be integrated in the complex systems being developed which could lead to a drastic improvement in the detectability rates using direct imaging.

The challenges of direct imaging

The most significant hindrance to direct imaging is the masking out of targeted planets and structures by bright quasi-static speckles. These speckles are a consequence of imperfections in optics and their effect becomes more dominant as the exposure time increases [10]. The dimensions of the speckles vary with the quality of the instrument. An example of this is that although speckles were predominant at 10" in the observation of Vega using the Gemini telescope [12], the observations undertaken by Masciadri et al. [13] were affected by speckles less than one second, using the Very Large Telescope. Furthermore, according to Lafrenière et al. [10], increase in exposure time does not correlate with an increase in contrast once the noise is affected by speckles, at a given angular separation. Subsequently, the quasi-static speckles need to be subtracted, which can be done using reference point spread function (PSF) images. The aim of using a reference image is to reduce quasi-static speckles, while simultaneously maintaining the targeted object. A variety of approaches, in the form of different post-processing algorithms exist for the development of as reference image from the series of images taken by the telescope.

Angular Differential Imaging (ADI)

The major techniques used to detect exoplanets by direct imaging include angular differential imaging (ADI) as well as spectral differential imaging (SDI) [9]. In ADI, images are captured with an altitude/azimuth telescope. The instrument field derotator (which is switched off), and the telescope are aligned and the field of view is permitted to be rotated with respect to the instrument. A relative point spread function can be developed for each image, considering the other images, which are subtracted to remove quasi-static speckle noise. In addition, basic transformations are carried out on the images to align them to the field, after which they are combined [12].

Spectral Differential Imaging (SDI)

In spectral differential imaging (SDI), spectroscopy is combined with coronagraphic imaging. A coronagraph is linked to an integral-field spectrograph in order to produce a dataset of one wavelength and two spatial dimensions. Similar to ADI, a PSF is constructed from each image, and the dependence of the function on the wavelength is manipulated in order to reduce the stellar contribution while conserving the spectrum and flux of the exoplanet [21].

The purpose of this study is to compare the effectiveness of the abovementioned PSF generating, post-processing algorithms and analyse their performance in varying imaging conditions. Subsequently, the in-depth discussion of each algorithm is conducted and the preferred imaging conditions are identified. Furthermore, the prospects of the applications of computer vision in astronomy are discussed. This study would lead to an ease in identification of a suitable algorithm for experimentation, depending on the scope of the experiment. Additionally, the limitations of the current algorithms identified in this study can be used in the development of novel algorithms, allowing the direct imaging method to adapt to the progress being made in terms of imaging capabilities.

Method of study

In the following sections, a non-mathematical introduction to principal component analysis (PCA) is provided. The algorithms are segregated based on the adoption of this approach. An in-depth review of the non-PCA algorithms is undertaken, followed by PCA algorithms and lastly, the RPCA based algorithm – LLSG [9]. In addition, based on the existing literature, PCA and non-PCA based approaches are compared and in particular, the impact of imaging conditions on the effectiveness of the algorithms is discussed. A common metric which can be used for comparison is the signal-to-noise ratio (S/N). However, under certain circumstances the noise can be almost totally minimized, which makes the ratio infinite. . Moreover, based on the comparison, current gaps in knowledge are identified. Furthermore, the prospects of the interrelation of computer vision, machine learning and astronomy are discussed in brief.

An overview of the algorithms

A lot of different approaches are utilized in the post processing stage of direct imaging - Projections on Karhunen-LoèveEigenimages (PKLE) [20], PynPoint [2]; the ANDROMEDA algorithm [16, 7]; GoDec[23] and SSGoDec algorithms [24]; LOCI algorithm [10], and the LLSG algorithm [9]. The three algorithms – LOCI, PynPoint and LLSG were selected for this study, based on their usability and applicability to, in particular, poor imaging conditions. These algorithms can be broadly segregated into PCA based (PynPoint), non-PCA based (LOCI) and RPCA (LLSG) based algorithm. This is done in order to observe how the two categories compare; and whether the current research focusing on Robust PCA (RPCA) algorithms is constructive.

Principal Component Analysis (PCA) and Robust PCA

PCA, also known as the Karhunen-Loève transformation (KLT), is a mathematical analysis technique, based on the assumption that each image in a collection can be expressed as a linear combination of its principal orthogonal components, depending on structures common to all images in the collection [15]. It is a least square estimation technique commonly used in various computer vision applications such as the expression of motions, shapes and appearances as parameters [8].

The major drawback of PCA is due to it being a least square estimation technique – outliers, which may commonly appear in direct imaging are unaccounted for. Consequently, Robust PCA (RPCA) approach was developed, which portray the data as superposition of constituents comprising background and foreground pixels [5].

As the usage of PCA is varied according to the algorithm, the mathematical approaches are analysed in depth for each. The PKLE algorithm [20], PynPoint [2], GoDec[23] and SSGoDec[24] utilize principal component analysis. The LLSG algorithm [9] adopts the RPCA framework. On the other hand, the ANDROMEDA algorithm [16], [7] and the LOCI algorithm [10] are not built on PCA, but utilize other analytical approaches used in computer vision.

II. Non-PCA based algorithm

"Locally Optimized Combination of Images" - LOCI algorithm [10]

Overview

The LOCI algorithm, developed by Lafrenière et al. [10], inputs one target image from which quasi-static speckles are to be reduced. The image is then segmented into subsections and a linear combination of reference images, which when subtracted from the target image will reduce the speckles, are obtained independently for each segment. It is assumed that N reference point spread function (PSF) images are available in order to reduce the noise. Depending on the impact of quasi-static speckles, the priority given to the reference images is optimized. As a consequence, a more accurate demonstration of the target image is obtained, compared to using a default amalgamation of exemplar PSF images. In addition, due to the dependence of the correlation between reference and target PSF images on spatial coordinates within the target images, it is recommended to enhance the coefficient of linear combination for segments of the target image.

Algorithm

Let S^T refer to the subsection wherein the coefficients used for reduction of noise within are obtained by minimization of speckles within a larger, optimization section, O^T. As the goal of the algorithm is to attenuate the quasi-static speckles, the ideal case would be the one where the subsections are one-pixel small. However, although a smaller subsection would lead to increased reduction in noise, it would also subtract the signals of the targeted sources. This is due to the dependence of the size of O^T on the preservation of the targeted point source signal.

The following algorithm and notation is verbatim from Lafrenière et al. [10].

The area A of the optimization subsection is given through the expression:

$$A = N_A \pi \left(\frac{W}{2}\right)^2 \quad (2.1)$$

where W refers to the full-width-at-half-maximum (FWHM) of the point spread function. Hence, N_A refers to the number of "PSF cores" in the optimization section.

The reference point spread function for optimization subsection is constructed according to

$$O^R = \sum_{k \in K} c^k O^k \quad (2.2)$$

Here, K refers to the subset of PSF images. As the exemplar image comprises of target images, it becomes essential to develop the enhanced function using the subset of the images in a given subsection wherein a companion point source would be displaced by a minimum distance δ_m or having intensity smaller by a minimum factor of α. This subset, K, consists of all reference PSF images of index k ∈ K, where

$$K = \{k \in [1, N] : |r_k - r_T| > \delta_m \ \vee \ {}^{f_k}\!/_{f_T} < \alpha \ \ (2.3)$$

Here, r_k refers to the position in image k, while r_T is a field position in the subtraction subsection of the target image. ${}^{f_k}\!/_{f_T}$ is the ratio of intensities of the targeted companion. The authors recommend customizing the selection of Na, delta-min and alpha, as they depend on the imaging conditions and quality.

The authors proceed to construct the reference PSF for the optimization subsection:

$$O^R = \sum_{k \in K} c^k O^k \quad (2.4)$$

The coefficients c^k are computed by the algorithm. This is done by minimizing the sum of the squared residuals of the subtraction of O^R from O^T. In other words, the variance is calculated. The minimum variance occurs when all of the partial derivatives with respect to the coefficients c^k are zero. By doing so, a system of linear equations is obtained, which on solving gives c^k, allowing the construction of enhanced reference PSF image for subsection S^T. As the matrix involved in the system of linear equation is always invertible, the system has a unique solution. This implies that the variance calculated is the absolute minimum of the residuals. Lastly, the optimized reference PSF image subsection is constructed as:

$$S^R = \sum_{k \in K} c^k S^k \quad (2.5)$$

S^k refers to the corresponding reduction subsection in the reference image k.

Analysis

The authors reported that the flux of point sources is drastically reduced at small separations. Consequently, it is essential to confirm the recovered flux and consider uncertainties. However, noise in the residuals may not be utilized as uncertainties in some cases. Due to this, artificial point sources for targets at small separations may be needed. Another noteworthy observation by the authors was that the "The fraction of the signal of a source that is subtracted by the algorithm is independent of the source brightness" [10].

The number of PSF cores (N_A) was the consequential parameter for this algorithm. This is because a smaller N_A correlated to a smaller signal-to-noise ratio. This is due to the insufficiency of gain in diminution of noise to compensate for the significant reduction in point source. Similarly, if N_A is too larger, the noise is not reduced effectively and the signal-to-noise ratio is again diminished. According to Lafrenière et al. [10], the optimum value of N_A is 300, which provides the best S/N ratio.

The authors report obtaining an S/N ratio of approximately 10, when in the range 22λ/D to 275λ/D, artificial point sources were appended to the images by steps of 2.75λ/D.

From the above analysis, it can be inferred that the algorithm is best effective when the distance to the source is large enough to not diminish flux. Additionally, the optimal value of the parameters, including N_A, is dependent on the quality of optical instruments, and the computational resources available.

Future applications

The LOCI algorithm is applicable not only to direct imaging of exoplanets, but can be used in applications for finding point sources with high-contract observations. Furthermore, it can also be used in simultaneous spectral differential imaging (SSDI) [17] as well as non-simultaneous spectral differential imaging (NSDI). In addition, the algorithm can be directly applied to the Fine Guidance Sensor on the James Webb Space Telescope [18], as it includes a tunable filter imager for NSDI [19] as well as a coronagraph for direct imaging of point sources [12].

III. PCA based algorithm

PynPoint [2]

The need for principal component analysis

Before analysing this algorithm, it is essential to understand why PCA is used and how it is superior to the methods preceding its introduction. A 'wavelet' analysis is frequently used in astronomy in the compression of images, filtration of noise and recognition of patterns. Wavelets can appropriately illustrate localized signals, as they refer to finite and fast-decaying orthogonal functions. Unlike traditional approaches, which require the image to be composed of small point-like sources, if it is to be compressed, the wavelet approach is flexible enough to be used with sources of different sizes [4]. Although PSF can be represented by wavelets, it cannot effectively capture the details of an image captured using high quality optimal instruments [25]. An alternative method, related to wavelets, shapelets can also be used for image processing. However, this approach narrows down the PSF, hindering it from capturing some advanced feature of the images. On the other hand, as PCA derives the relevant basic functions from the data itself, this results in a significantly smaller number of functions [25].

Consequently, PCA has been extensively used in large surveys, including the Sloan Digital Sky Survey (REF). In PCA, the components with lowest variances are the most affected by quasi-static speckles and can be disregarded. This makes it a powerful tool for image processing, allowing complex images and spectra to be expressed with a few principal components [11].

PynPoint (Software package)

The PynPoint package follows the four main steps in order to process high-contrast images of exoplanetary systems:

1. Construction of a basis set for the analysis
2. Connection of the stellar PSF to each image
3. Correction for PSF and central star
4. Averaging over a stack of images

PCA coefficients, a_i are calculated using the basis function:

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$$a_i = \int I(x)\phi_i(x)d \quad (3.1)$$

Where I(x) is the image of the point spread function and $\phi(x)$ is a given basis

[2]

Analysis

Although a number of popular basis functions are extensively studied, for example, decomposition of shaplets into Gaussian weighted Hermite polynomials; and Fourier decomposition into trigonometric functions,the authors of PynPoint adopted the approach of creating a basis set from their data. This leads to a smaller number of coefficients needed to make the residuals between the model and image under a certain margin, hence making this approach significantly efficient compared to using ready-made basis functions.

The PynPoint analysis has one free parameter of consequence which is set by the user – the number of PCA coefficients for every image. Consequently, the signal to noise ratio varied between the range of 15-20, when the parameter was between 20 and 60.

The authors optimized the PCA by treating the data before application. This was done using subpixel sampling, wherein features were reconstructed with resolution greater than that of a singular image. Furthermore, the central region, which influences the flux of the image, was masked. Each of the images in the stack was subtracted by the mean image, which is generated from the stack. The application of PynPoint and the preceding optimization resulted in a signal to noise ratio of approximately 20, when the publicly available, 2009 L'data for the exoplanet βPictoris b was analysed.

IV. RPCA based algorithm

LLSG algorithm [9]

Overview

Some drawbacks of traditional PCA model included a lack of versatility and high computational costs for graphical data [5]. Consequently, the Robust PCA (RPCA) model was developed. RPCA describes the data as superposition of sparse and low-rank components constituents comprising of foreground and background pixels respectively.

The principal component pursuit (PCP) algorithm developed by Candès et al. [6] was a premier proposal to solve the decomposition. In PCP, a matrix M, whose columns are vectorised version of *n* images, is fragmented into low-rank (L) plus sparse (S) [L+S] matrices by solving:

$$\begin{array}{ll} m & \|L\|_* + \lambda\|S\|_1 \\ s & t \;\; L + S = M \end{array}$$

(4.1)

The ideal scenario would be the one where the sparse component captures the small, moving planets; while the low-rank components capture the reference PSF. However, while analysing real angular differential images, the authors report that the reference point spread function, due to quasi-static speckles, is never low rank. Consequently, the fragmentation into low-rank plus sparse components is never exact. Hence, the target image using PCP, after being affected by noise due to quasi-static speckles, is similar to those produced using principal component analysis.

Algorithm

As stated by Gonzalez et al. [9], the algorithm follows four major steps:

1. Images of the cubes are fragmented into patches, in quadrants of annuli of width 2 λ/D.
2. The quadrants are independently decomposed as per the below equation. This updates L and S components for a fixed number of iterations, alternatively.

$$\begin{cases} L_t = \underset{r\ (L)\le k}{\operatorname{argmin}} \|M - L - S_{t-1}\|_F^2 \,; \\ S_t = \underset{c\ (S)\le c}{\operatorname{argmin}} \|M - L - S_{t-1}\|_F^2 \,. \end{cases} \quad (4.2)$$

3. The S component of decomposition is kept for each patch.
4. After rotating to a common north, all of the patches are median combined in a final image.

Analysis

The rank parameter is the most important parameter in LLSG, comparable to the number of principal components in PCA. The definition of the size of the low-rank approximation is provided for the dataset by this parameter. If the value of the parameter is low, in the sparse tern, the noise is not reduced effectively. In contrast, if the value is too high, the planetary signal is reduced by the low-rank term. Additionally, the number of iterations can be varied. The authors set the default value of the iterations to 10, as per their sample data set. However, it is important to note that the number of iterations is directly proportional to the computing time.

A drawback of the full-frame PCA approach was its inability to enhance the signal-to-noise ratio simultaneously for each exoplanet in a single image, by adjusting the number of principal components. Gonzalez et al. [9] utilized PCA low-rank-approximation annulus-wise. According to Absil et al. 2013, this makes the application of a parallactic angle based frame-rejection criterion possible. As a consequence, the background and quasi-static speckles can be aptly reduced for a particular patch.

When executed with data from βPictoris b, the highest S/N ratio obtained was 16.7, using 38 principal components [9]. Instead of the traditional definition of S/N, the authors implemented the one proposed by Mawet et al. [14], which take into account the issues of application of small sample statistics to small-angle high-contrast imaging.

According to Gonzalez et al. [9], the ability of this algorithm to process a typical pixel cube without compromising computational resources makes it superior to the PCA based approaches. Furthermore, the patches can be processed by different computers. This utilization of multi-core architecture of computers could lead to real-time processing and analysis.

V. Comparisons

Although a lack of standardisation of signal-to-noise ratio definition, and the difference in imaging conditions and optical instruments used to assess the algorithms in their respective studies, a quantitative comparison of the algorithms becomes onerous. Nevertheless, Gonzalez et al. [9], argue that the ability of the LLSG algorithm to process typical images without incurring extensive computational costs makes it indispensable to the progress made in terms of optical and imaging capabilities. This is further strengthened by the ability of separately processing each patch, hence utilizing the immense extent of multi-core computers. Furthermore, when the performance of the algorithm was compared with PCA algorithm using receiver operating characteristic (ROC) analysis, it was found that the true positive rate (TPR) of LLSG was 83%, compared to 55% in the case of PCA [9].

However, the major drawback of the LLSG algorithm is that it has a negative impact on the signal of potential exoplanets. Consequently, the flux of the exoplanets cannot be estimated using the final LLSG frames. Additionally, for calibration of photometry of potential bodies, negative companion candidates have to be inserted [9]. This leads to the identification of a current gap of knowledge – the current model of quasi-static speckles needs to be enhanced in order to formula better algorithms.

Amara &Quanz [2] conducted a comparison between the LOCI algorithm and PynPoint. Two cases are considered where the contrast between the exoplanet and its host is 8.0 mag and 10.5 mag. For planetary position greater than 0.29 arcsec, it was found that PynPoint leads to a 50% improvement in S/N. Detection of planets which are 0.5 to 1.0 mag fainter than those detected by LOCI is made possible in case of PynPoint. Additionally, at a separation of approximately 0.29 arcsec, the S/N ratio is increased by a factor of 5 in case of PynPoint. This implies that PCA based algorithms such as PynPoint are able to detect exoplanets more effectively compared to non-PCA based algorithms such as LOCI.

Conclusion

This review focused on three algorithms which utilized three different approaches. The concept of principal component analysis, used by the PynPoint software [2] was explained. Additionally, the robust PCA approach, utilized by the LLSG algorithms [9] was discussed. The algorithm with a non-PCA approach, the LOCI algorithm [10] was superseded by PCA, under the circumstances of the study conducted by Amara &Quanz [2]. Regardless, using ROC, the LLSG algorithm was found to be more effective than PCA based algorithms. However, the LLSG algorithm, despite its effectiveness, needed insertion of negative companions for photometric calibration. Furthermore, the signal of the exoplanetary system was significantly reduced by the algorithm. By analysing the LLSG algorithm, it was found that more research needed to be conducted in order to fine tune the model of noise in order to develop algorithms that can enhance the detectability of exoplanets.

With missions such as James Webb Space Telescope and WFIRST, the imaging capabilities and quality is expected to significantly improve. Consequently, the optimization of algorithms and development of novel approaches is quintessential to boost the detection of exoplanets by direct imaging.

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