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Faint Companion Detection Using Noise Removal with Speckle Interferometry

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Abstract. I use simulated adaptive optics data to demonstrate a noise removal technique exploiting prior knowledge of the angular support of the object. Using both detector-noise limited and speckle-noise limited data, I show that this method can result in significant increases in the sensitivity of speckle interferometry to faint companions under demanding observing conditions.

1. Introduction

Adaptive optics (AO) is a powerful tool in the hunt for faint companions in star systems, reducing dramatically the size of the primary's blur angle and exposing dim objects (Close et. al. 2002; Liu et. al. 2002; Potter et al. 2002). However, use of AO with relatively dim guide stars typically yields significant PSF halo either from wavefront sensor (WFS) noise or poor deformable mirror (DM) fitting. As a result, post-detection deconvolution is typically required to increase image resolution to significant levels. Performance of all such algorithms, however, is fundamentally limited by the data SNR. Further, observing a dim primary can mean resolution is effectively limited by detector noise regardless of AO performance, and conventional deconvolution processing can do nothing to overcome this limit.

My colleagues and I are currently researching ways to incorporate prior knowledge about the object in deconvolution algorithms to reduce noise. So-called penalty functions, ostensibly representing prior knowledge, have been used in iterative algorithms for some time, but only to limit noise amplification by constraining estimated object intensity maps to have, say, some maximum curvature or minimum smoothness ("entropy"). Limiting noise amplification, however, is not the same as reducing noise, and such constraints are rather *ad hoc* and have only a tenuous basis in physics. Further, use of penalty functions to regularize maximum-likelihood solutions inevitably requires the user to subjectively select a weighting parameter for the penalty. These facts make it difficult to argue that the constraints discussed actually *add any information* to the measured data.

A more compelling case can be made for the use of an image support constraint in a convex projection algorithm (Matson 1994; Tyler & Matson 1997). An image support is the area outside of which all measurements are known to be noise; the information added to the measured data is knowledge of the angular extent of the object. In this paper, I demonstrate the use of a convex projection algorithm to remove noise from image energy spectra, resulting in a strong increase in the sensitivity of speckle interferometry to faint companions.

Speckle interferometry (Labeyrie 1974) is a time-tested technique for direct detection of stellar companions. The method yields an estimate of the image energy spectrum with significant signal to a large fraction of the diffraction limit. The Fourier transform of the energy spectrum, the image autocorrelation, yields separation and relative magnitude data for a binary star system. Speckle interferometry continues to be used along with bispectrum speckle imaging to produce significant astrophysical results, including very recent results from Keck I observations (Monnier et. al. 2002; Tuthill et. al. 2002). More relevant to this conference, speckle imaging has been used with Keck I data to hunt for brown dwarfs (Kuchner et. al. 1998). Although the concepts presented here can be used with other algorithms, I have chosen speckle interferometry to demonstrate the use of support to remove noise for the following reasons: First, the use of AO to acquire speckle data has been shown to both radically reduce the number of frames required to build up reasonable SNRs (Roggemann et. al. 1994; Matson et. al. 2002) and dramatically increase practical exposure times; second, speckle interferometry is free from insidious artifacts that can plague Richardson-Lucy (Michard 1996); and finally, speckle interferometry estimates the energy spectrum, which is much less strongly filtered by residual turbulence than the object Fourier spectrum.

In Section 2, I describe the convex projection algorithm as well as the simulation used to synthesize AO image data. In Section 3, I show results for detector noise and speckle noise-limited cases and discuss their significance.

2. Data simulation and processing

The angular support of an object is constrained by setting to zero all image pixels outside the support. This action is identical to multiplication of the original image by a function that has unit value inside the support and is zero elsewhere. As a result, the Fourier spectrum of the constrained image is the convolution of the spectrum of the unconstrained image and the spectrum of the support function. The energy spectrum and autocorrelation of an image are also a Fourier transform pair, so the same statement applies to the use of an autocorrelation support. Since the support of an image autocorrelation is simply related to the image support, the concept moves easily to speckle interferometry.

Two phenomena result when support is applied. The first is *noise scaling* and results naturally from Parseval's theorem when all pixels outside the support are set to zero. The noise level in the energy spectrum is reduced by the factor $\frac{A_s}{A_d}$, where A_s is the area of the support and A_d is the area of the field of view. The second is *noise transport*, arising from the convolution of the energy spectrum and autocorrelation support spectrum. Convolution smooths the noise distribution, with the result that noise is redistributed from "sources" (frequency bands with relatively high noise levels) to "sinks" (frequency bands with relatively low noise levels). After this smoothing, one constrains the energy spectrum noise to be *no larger* than the variance prior to the application of support. The application of this conjugate constraint actually results in a reduction

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of noise *inside* the autocorrelation support (the noise outside the support has already been eliminated by applying the support). The code to execute this algorithm is written in Fortran 90 and is part of a larger code that calibrates short exposure data, forms debiased image and reference star energy spectra, and performs the Labeyrie deconvolution.

The AO simulation generates random realizations of Kolmogorov phases. Wavefront slopes are calculated by a contour integration around the subaperture edges. Noise is added to the slopes according to an analytical formula using the rms read noise, guide star magnitude, and the ratio of the subaperture width and r_o. The reconstructor matrix is factored in an off-line calculation so system modes can be filtered. In the detector model, thermal current buildup, sky background, shot noise, and read noise are simulated. Currently, servo lag is modeled by adding equivalent noise to the wavefront measurement.

3. Results

I have generated two data sets representing difficult observing conditions. Data SNR in the first case is limited by detector noise; that is, the AO system is working reasonably well, but the object is rather dim. These conditions could be encountered either observing a dim primary with a laser guide star or observing a primary significantly brighter in the AO WFS band than in the imaging band. In the second case, data SNR is limited by speckle noise, with the primary being reasonably bright in the imaging band and dim enough in the WFS band to require reconstructor mode filtering. The speckle noise limit may also be encountered in severe seeing or if a number of system modes are filtered to eliminate "waffle" artifacts.

The simulated AO system has 40 Shack-Hartmann subapertures with 42.5 cm lengths and 49 DM actuators spaced 45 cm apart. The primary mirror is 3.6 m in diameter. The AO guidestar for the detector-noise limited (DNL) case has an R magnitude of 12, giving an SNR in the WFS of over 4 at a bandwidth of 30 Hz. The primary magnitude is H=16, giving about 9000 counts per 300 ms camera integration. For the speckle-noise limited case (SNL), the primary brightness is increased by 1.6 magnitudes, giving about 39,000 counts per frame. The AO guidestar magnitude is increased by a magnitude, giving a WFS SNR of under 2. Because an SNR this low typically will not allow stable closed-loop AO operation, the highest 19 reconstructor singular modes are zeroed using the mode filter. The Strehl ratios are 0.163 for the DNL case and 0.096 for the SNL case.

My results are shown in Fig. 1. The image support is a simple $1''.6$ (15 pixel radius) disk around the primary. Thirty frames were used for the DNL case and 10 frames for the SNL case. Azimuthally-averaged energy spectrum SNR curves are plotted to show where the SNR goes below unit value, the effective spatial resolution limit for the associated autocorrelation. For the DNL case, noise is uniformly distributed across all spectral bands. The noise reduction, primarily due to noise scaling, results in a factor-of-five increase in the SNR at all frequencies. To produce this increase with more data frames would require an additional 720 frames. The resulting increase in the "SNR cutoff" from 0.4 to 0.63 times the diffraction limit means the energy in the autocorrelation peaks

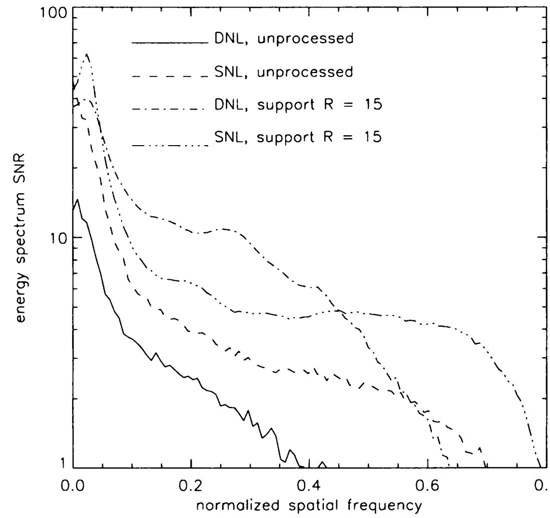

Figure 1. Energy spectrum SNR curves before and after noise removal processing for DNL and SNL cases.

representing a companion can be concentrated into an area 2/3 smaller than before processing, raising the amplitude of the companion peak by ≈ 2.25. The SNL curves show a larger increase after noise removal at high frequencies than at low, indicating the frequency dependence of speckle noise and the effect of noise transport. While the cutoff increase is not as significant for the SNL case, the ratio between SNL curves still represents a noise-equivalent resolution increase of 1.9.

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