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Thoughts about disentangling in wavelength and in Fourier-space

Saša Ilijić

Deptartment of Applied Physics, Faculty of Electrical Engineering and Computing, University of Zagreb, Unska 3, HR-10000 Zagreb, Croatia

Abstract. The spectral disentangling technique can be understood as a two-level least-squares problem. The lower level, known as spectral separation, is a linear least-squares problem where the spectra of component stars are reconstructed from a time series of spectra of a multiple stellar system, given the RVs of component stars in the observed spectra. In the upper level the parameters of orbit are optimised in order to find the setup of RVs that yields the best fit at the separation level. Spectral separation implemented in wavelength-space is computationally less efficient than in Fourier-space, but offers larger flexibility in sampling and weighting of the data. The two implementations of the separation algorithm may respond differently to systematic noise in the data such as phase correlated inconsistencies in normalisation of the observed spectra.

1. Introduction

The spectral disentangling technique, introduced by Simon & Sturm (1994) and independently Hadrava (1995), SS94 and H95 hereafter, takes a time series of spectra of a multiple stellar system as input and yields a self consistent solution to the parameters of orbit and the spectra of component stars. The method is based on the assumption that the component spectra are time-independent and it does not use spectral templates for component stars.

At the heart of the disentangling method is the spectral separation algorithm that, given the time series of composite spectra and the orbital RVs and fractional light-contributions of component stars, reconstructs the spectra of component stars. The first spectral separation that did not rely on the template spectra was the 'tomographic separation' of Bagnuolo & Gies (1991), BG91 hereafter, who formulated the problem as a large-scale linear least-squares fit to the data. In their approach the number of coupled equations to be solved equals the total number of data points in the composite spectra, and the number of unknowns is the number of amplitudes in the component spectra. BG91 used an iterative technique to solve the system of equations while SS94 used the singular value decomposition (SVD) to handle the rank-deficiency of the system in a more robust way. Additionally, SS94 introduced disentangling by optimising the parameters of orbit of the binary. H95 expressed the separation problem in terms of the discrete Fourier transforms of the data which allowed him to uncouple the large system of equations. The Fourier-space separation algorithm of H95, for further developments see e.g. Hadrava (2004) and Ilijić et al. (2004), is simpler to implement and use and is computationally more efficient than the wavelength-space algorithms of BG91 and SS94. However, the λ-space algorithms have several interesting features unavailable in the Fourier-space.

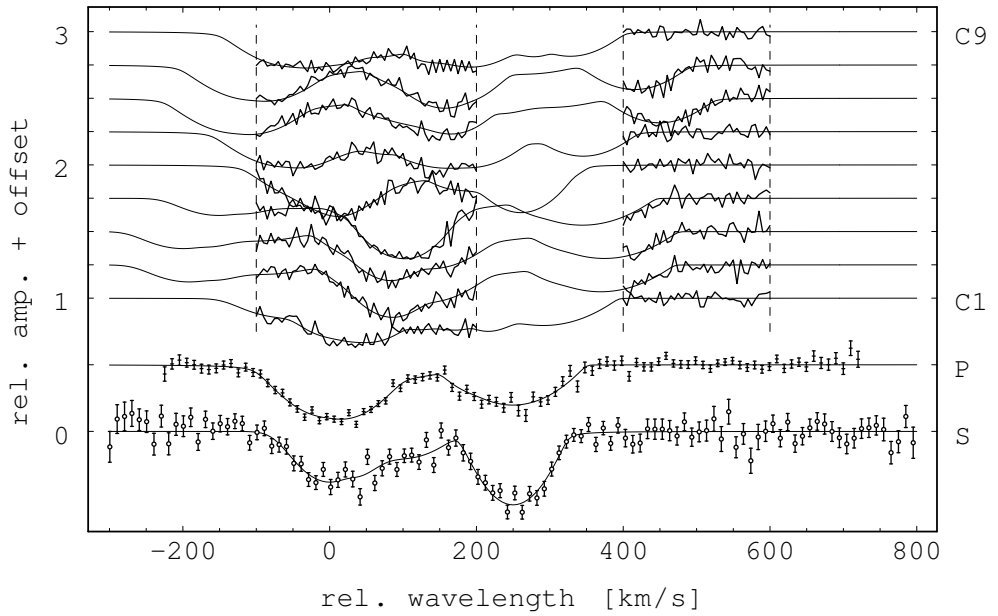

Figure 1. Functions P and S constructed from rotationally broadened lines, $v_{P,S} \sin i = 100, 75\,\mathrm{km\,s^{-1}}$, are RV-shifted and added to form artificial composite spectra C1–C9 at randomly chosen orbital phases using $K_{P,S} = 125, 200\,\mathrm{km\,s^{-1}}$ and flux-ratio 2:1. Discrete data is simulated in two spectral windows at sampling rate of $5\,\mathrm{km\,s^{-1}}$, $S/N = 25$. The component spectra reconstructed in λ-space are shown with symbols and error bars over P and S.

2. Fourier vs. λ-space separation algorithm

The computationally efficient spectral separation in Fourier-space is possible under these constraints: (1) all observed (input) spectra are sampled on the identical grid of points distributed equidistantly in the logarithm of the wavelength, (2) all data points within one observed spectrum are assigned equal fitting weight and (3) under the RV-shifts the model component (output) spectra behave as periodic (cyclic) functions of wavelength. The constraint (1), in general, requires resampling of data from the original resolution of the detector to the working grid. Due to (2) any systematic effects in the data (e.g. interstellar or telluric absorption, detector blemishes) should be corrected for since they can not be masked in the fit. The non-physical behaviour of the model (3) at ends of the spectral range is acceptable only if the ends of the working spectral range can be placed in the continuum regions far enough from the spectral features of interest.

The λ-space algorithms of BG91 and SS94 were formulated under the constraints similar to (1) and (2), but not (3). Instead of using cyclic component spectra the λ-space algorithms extend the model spectra at both ends of the spectral range as far as is necessary to fit the data under all required RV-shifts. Interestingly, the λ-space algorithms can be formulated even without requiring (1) and (2). One can allow each observed (input) spectrum to be sampled on

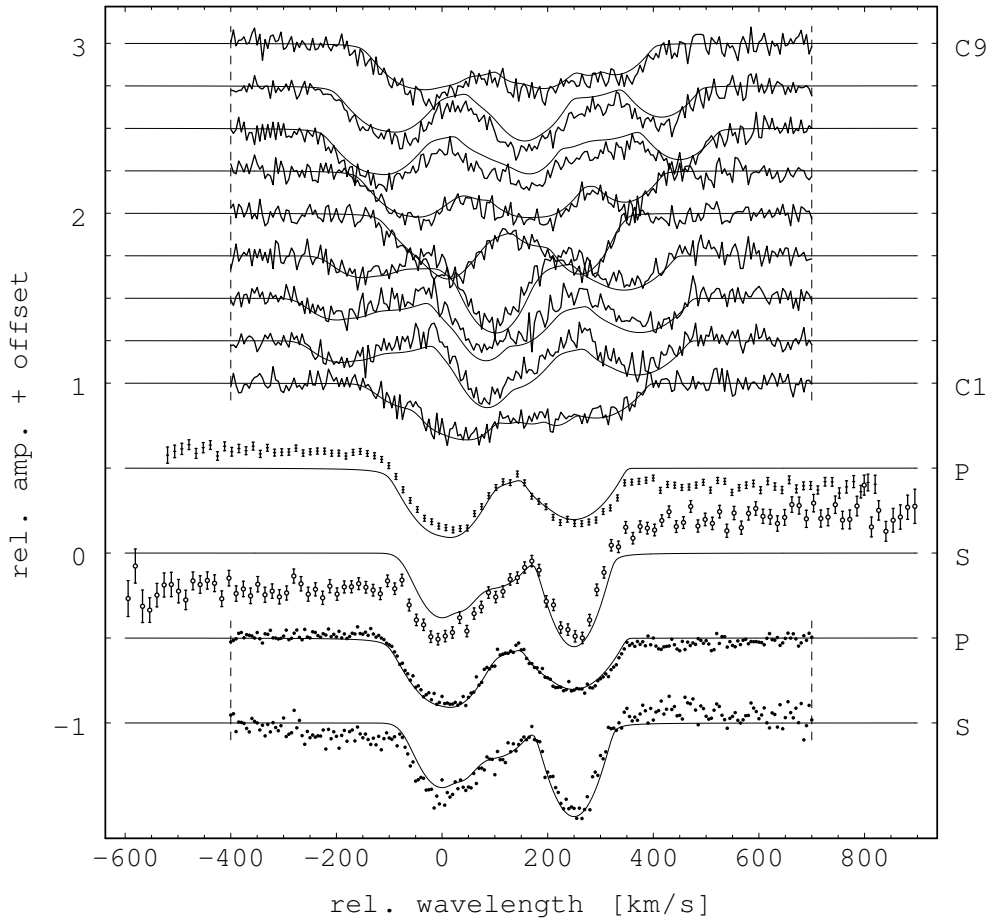

Figure 2. The data is simulated as is Fig. 1 but with systematic error in normalisation. The upper P and S pair shows the reconstruction of component spectra in λ-space and the lower pair in Fourier-space.

its own grid and each data point to be weighted independently. In practice this means that the original resolution and spectral coverage of the detector(s) can be preserved, and that the errors estimated during the data reduction can be used to provide fitting weights. The ability of the λ-space algorithm to handle irregularly sampled data is demonstrated in Figure 1. The gap between the two data windows is only a little narrower than the upper limit that would still allow uninterrupted reconstruction of the component spectra, for a binary in a circular orbit and fair phase coverage this is is $2K_{\rm P}$ (assuming $M_{\rm P} > M_{\rm S}$). Also note that at outer ends of the data windows the reconstructed components span out almost one RV-semiamplitude. Another useful feature of λ-space separation algorithm are the error estimates on the amplitudes of the reconstructed component spectra. Among other things these depend on the resolution at which the component spectra are reconstructed.

3. Propagation of systematic noise: an example

Relatively faint systematic effects in the data, perhaps hidden in the random noise, may lead to much stronger effects in the output. A likely effect in a time series of observed spectra is inconsistent normalisation correlated with orbital phase (Hensberge 2004). In the simulated data set of Fig. 2 the spectra are correctly normalised in the continuum regions while in the absorption regions the error is proportional to RVs of the stars. As can be shown by a simple calculation, the component spectra might respond to this kind of effect in the data with artifact slopes of opposite signs. Indeed, in λ-space we obtain the artifact slopes in the line region, and not in the continuum region. However, the slopes 'accumulate' an amplitude shift over the affected region and the continua at the two sides end up at different levels. The Fourier-space separation develops less slope in the line region, but it also bends the continuum regions in the other direction. This is the consequence of the cyclic definition of component spectra. Their ends are connected one to another, as are any other two neighboring points, so the algorithm forces them to the same level to avoid the discontinuity. The Fourier-space algorithm may occasionally appear as more robust, but the error propagation is harder to follow and the risk of artifacts being present and going unnoticed is increased.

4. Concluding remarks

In a disentangling procedure, the speed of Fourier-space algorithms allows using large data-sets and exploring a wide range of orbital parameters space. λ-space disentangling might improve a solution which is near to the optimal one. Focusing on the output component spectra, in applications to short spectral regions of complicated spectra, λ-space algorithms are more appropriate. The two approaches are, in this sense, complementary. This research used the Fourier-space disentangling code FDBinary (Ilijić et al. 2004) and the λ-space separation code CRES (`http://sail.zpf.fer.hr/cres`), both freely available.

References

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