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Using spectrotiming analysis to eliminate spectral degeneracies

The case of Cyg X-3 and other X-ray binaries

Modeling the X-ray spectra of X-ray binaries (XRBs) often leads to a problem of degeneracy, i.e. multiple distinct models fit the observed data equally well, despite the excellent quality of the available data. In order to make sense of this degeneracy we need to take other data dimensions besides the spectral into an account. For this need X-ray timing data is readily available, and several methods have been developed to combine spectral and timing analyses. Here we review a method where the variability components of the X-ray spectra are revealed by employing principal component analysis to single out individual emission components causing the variability in the X-ray lightcurves across the spectral range. We have studied several XRB systems using data from RXTE and we show that most of the spectral variability of all sources can be attributed to two principal components. In two sources, Cyg X-3 and GRS 1915+105, the dominating principal component is 'soft' while in two other sources, GX 339-4 and Cyg X-1, it is 'hard'.

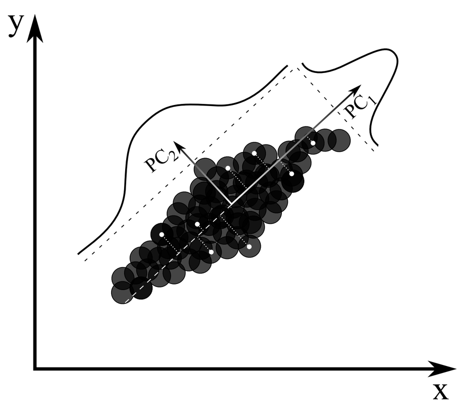
Method

Principal Component Analysis (PCA)

PCA is used here as a variability analysis tool which allows one to combine temporal and spectral information to identify various components of the spectrum based on their variability.

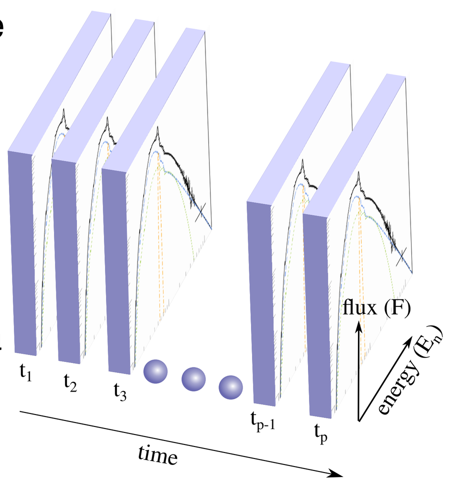
1

PCA finds patterns in a way that highlights the differences and similarities in the data set. By finding the "new coordinates" of the data set (i.e. the principal components) where the data points mainly cluster and ignoring the small scatter in other directions the dimensionality of the dataset is reduced, defined only by a few of these new coordinates.



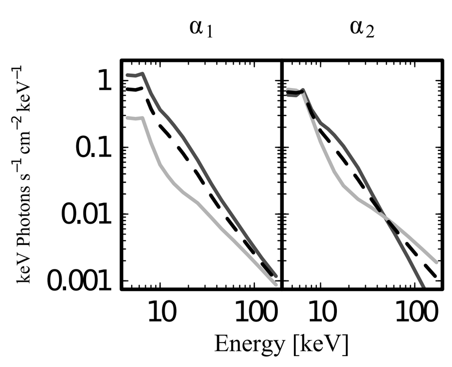
2

We applied PCA to sets of X-ray spectra following the procedure presented in Malzac et al. (2006). One starts with calculating a covariance matrix from a stack of spectra $F(E_n)$ measured at times t_p, stating the variances between each n-dimensions. The eigenvectors of the covariance matrix form the "new coordinates" of the data and the accompanying eigenvalue states its proportion of variance. The data can then be expressed as a linear decomposition using only the most significant eigenvectors portraying the intrinsic variability of the data set.



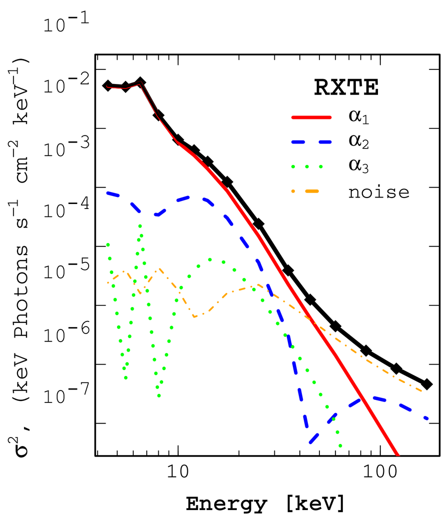
3

The eigenvectors can be examined to determine their influence on the energy spectrum. If all the evctor components have the same sign, the effect on the energy spectra is similar in all energy bands, i.e. the normalization of the spectra changes. If the vector components have opposite signs the effect on the energy spectra is a pivoting around a certain energy band.



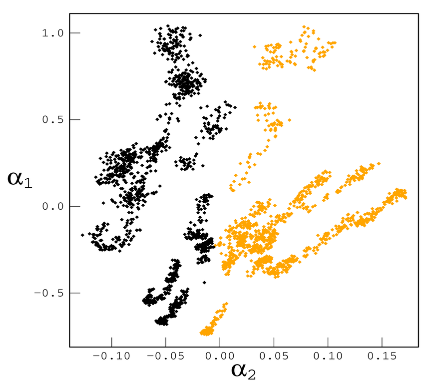
4

Based on the significance order of the eigenvectors a variability spectrum can be constructed. This shows the energy-dependent variance across the energy range and can be related to the r.m.s. as r.m.s.(E) = σ(E)*F(E). Most of the source variance is typically attributed to two or three components with differing proportions along the energy range.



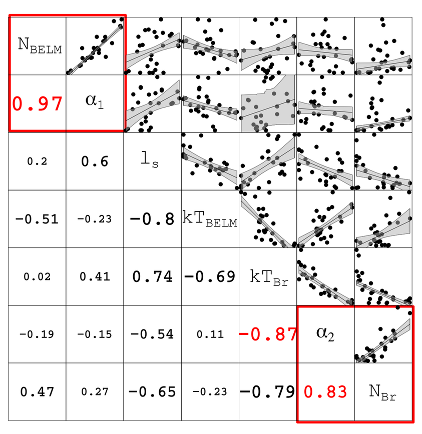
5

The "normalization" of principal components can be plotted against each other in a so-called "scores plot". This can be used to determine how the components evolve during the time period in question, and whether there exists clustering for different states. On the left an example is shown where different spectral states have been colored in order to see the effect of the principal components. In this case a change in the second principal component (α_2) drives the spectral state change.



6

The averaged "normalization" or scores of the principal components over the individual pointings can be compared to the model fits. This can be used to determine the component or the parameter causing the variability. If the effect of a principal component on the energy spectra is equal in all energy bands then this will most likely correspond to a model component normalization parameter. If the effect is pivoting then it might correspond to some other parameter as well. This in turn can be used to rank models that do not exhibit correlations with the principal components.



References:
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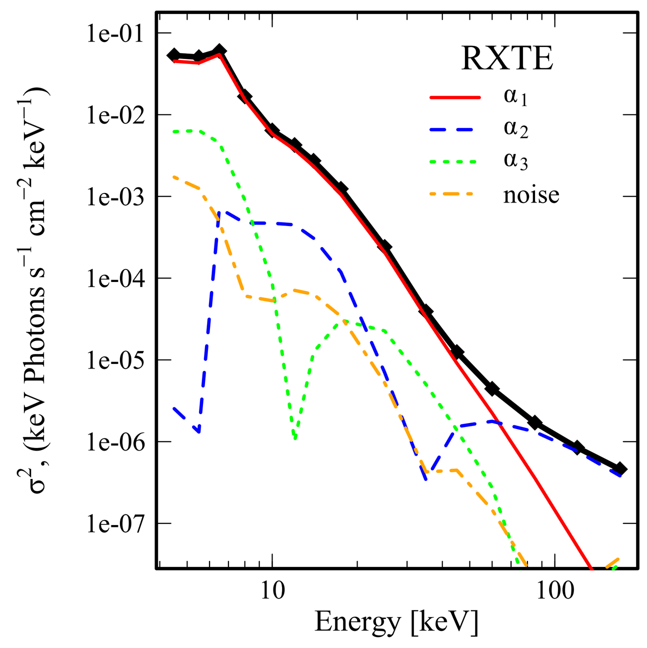
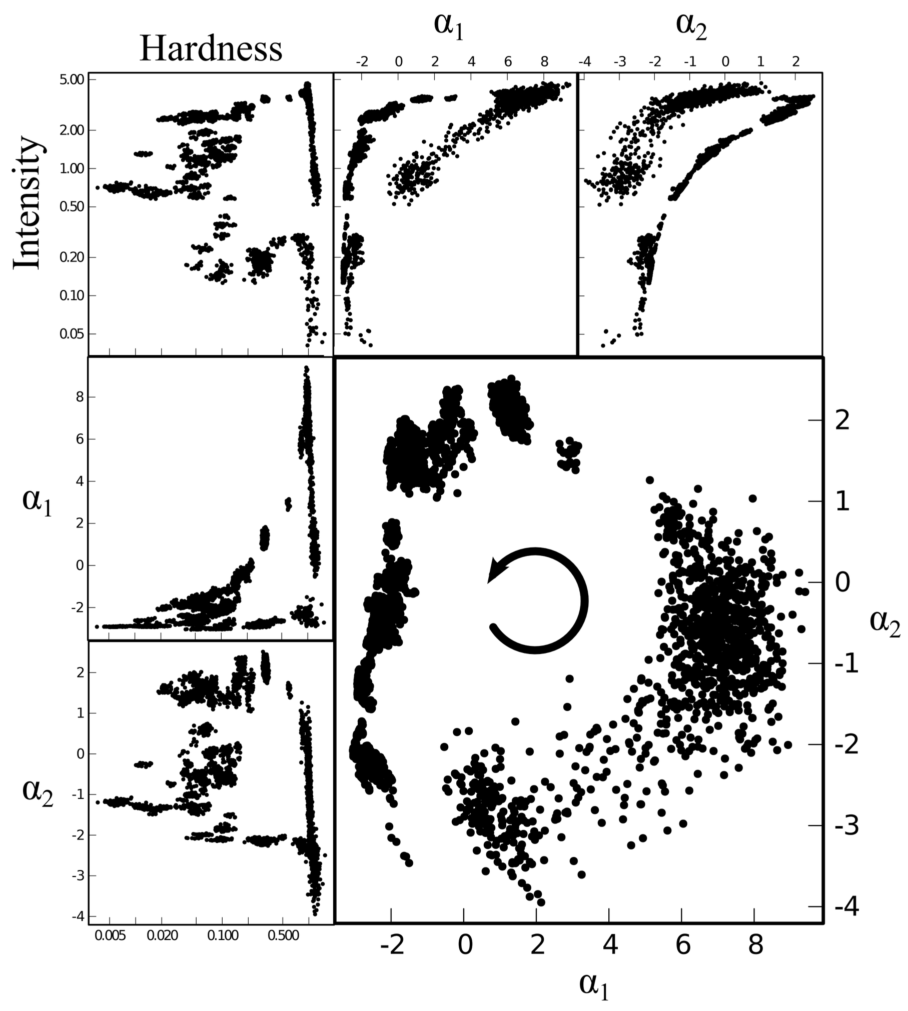
Cyg X-3

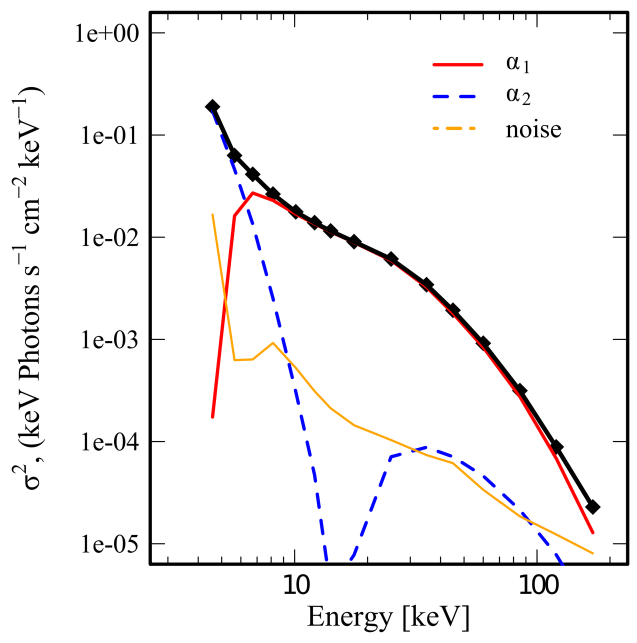
- 2 major principal components (proportions of variability: α_1~68%, α_2~23%)
- Data from a major radio flare episode (i.e. intermediate X-ray spectra)
- Most of the variability is caused by the 'soft' component
- The principal components can be attributed to two emission components: inverse-Compton scattering and bremsstrahlung (see Method 6)
- Similar to GRS 1915+105
- Koljonen et al. (2013)



GX 339-4

- 2 major components (α_1~82%, α_2~15%)
- Data from 2002/2003 outburst (e.g. Belloni et al. 2005)
- most of variability caused by the 'hard' component
- similar to Cyg X-1
- spectral modeling ongoing
- Koljonen et al. (in prep.)

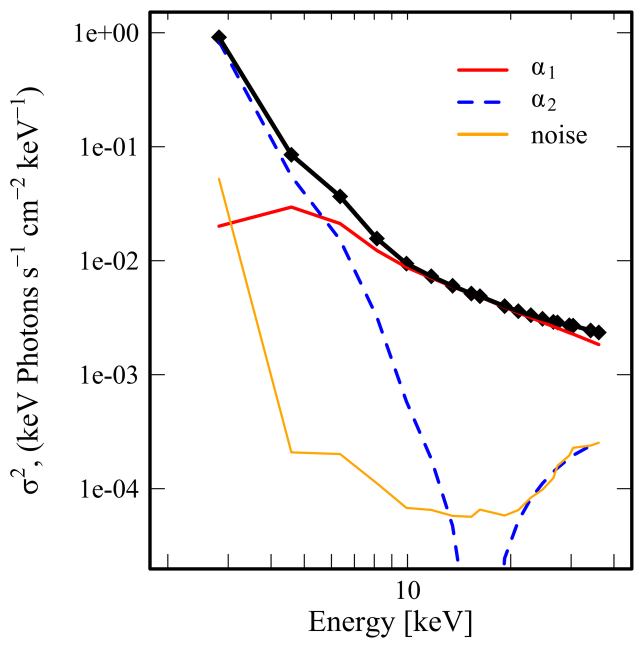




- Both principal components show hysteresis
- The normalization of α_1 increases in the LH state and decreases when the spectra softens
- The normalization of α_2 increases in the LH state, stays constant in the intermediate state and decreases slowly in the HS state

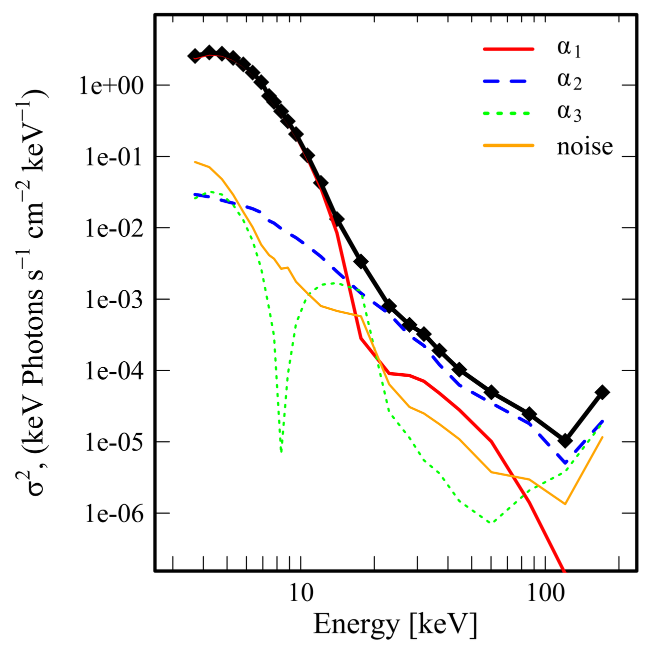
Cyg X-1

- 2 major components (α_1~82%, α_2~15%)
- All data from RXTE epoch 3
- note just RXTE/PCA data
- most of variability caused by the 'hard' component
- similar to GX 339-4
- spectral modeling ongoing
- Buchan et al. (in prep.)



GRS 1915+105

- 2 major components (α_1~62%, α_2~26%)
- Same dataset as in Belloni et al. (2000)
- most of variability caused by the 'soft' component
- similar to Cyg X-3, but the second component more stronger in the hard X-rays
- spectral modeling ongoing
- Peris et al. (in prep.)



Implications

PCA shows that only two components are needed to explain the spectral variability of the above-mentioned XRBs. Thus, in principle only two 'variables' would be needed to fit the X-ray spectra throughout the spectral evolution of the sources. It is tempting to attribute these to the accretion disk and the corona directly on indirectly. However, for Cyg X-3 the best-fitting model satisfying the principal component evolution included Comptonization and bremsstrahlung, so clearly these systems can have separate emission components from each other. This work to attribute spectral models to the spectral variability is ongoing.