X-Ray Source Detection Using the Wavelet Transform

P. E. Freeman, V. Kashyap, R. Rosner, R. Nichol, B. Holden, D. Q. Lamb

Department of Astronomy and Astrophysics, University of Chicago, Chicago, IL, 60637

Abstract. We present a new method that uses the Mexican Hat wavelet transform in a particularly simple manner to detect X-ray sources. We use an iterative approach to correlate data with the Mexican Hat function and to cleanse suspected sources from the data. This allows us to estimate the background and specify a threshold for source detection in the correlation map of the original (uncleansed) data. This method is valid in the Gaussian limit of high background counts and assumes that the background does not vary over the instrument field-of-view. Application of this method to simulated data of the ROSAT PSPC show it to detect X-ray sources more sensitively than a method in which we calculate \( S/N \), and its use with ROSAT PSPC data of the Pleiades Cluster results in the detection of \( \approx 30 \) X-ray sources not detected with the \( S/N \) method.

1. Introduction

The wavelet transform is a powerful new tool for the detection of astronomical sources (Slezak, Bijaoui, & Mars 1990; Rosati et al. 1995). In contrast to classical source detection methods, it allows simultaneous study of the shape, location, and strength of sources. The wavelet function most used for source detection is the Mexican Hat (MH) function, which in its rotationally-symmetric form is proportional to the second derivative of a two-dimensional symmetric Gaussian function of width \( \sigma \):

\[
F(r) = \left(2 - \frac{r^2}{\sigma^2}\right) e^{-\frac{r^2}{2\sigma^2}}.
\]

(Radial symmetry, assumed in this paper, in not a necessary condition on the use of the MH function.) It has a positive core of radius \( \sqrt{2}\sigma \), encircled by a negative annulus such that the normalization of the function is zero (Figure 1).

The MH function has many useful properties. Its negative annulus serves as a natural background subtractor. Also, its shape allows it to act as a filter, preferentially enhancing features in the data that have scale size \( \sim \) \( \sigma \). This filtering property of the MH function aids the analysis of data with sources of various sizes. Last, the MH function has limited extent in both the spatial and Fourier domains, minimizing aliasing problems during correlations.

In this paper, we present a method which uses the MH wavelet transform in a particularly simple manner to detect X-ray sources. More general methods may be found in Damiani et al. (1996) and Freeman et al. (1996). The latter
paper discusses the source-detection software code WDETECT, being developed for the Data Analysis System of the Advanced X-ray Astrophysics Facility (AXAF) (Conroy et al. 1996).

2. Algorithm

We compute the correlation, $\nu$, of data using the correlation theorem: we compute the product of the FFT of the data and the FT of the MH function, and take the inverse FFT of this product to determine $\nu$. The differential distribution of $\nu$ for all pixels is quasi-Gaussian, with mean zero (Figure 2), if the expected number of background counts per pixel, $B$, is such that $2\pi\sigma^2 B \gtrsim 1$. A tail on the positive half of this distribution indicates sources in the data (Figure 2). To determine if a particular pixel $(x, y)$ belongs to an X-ray source, we compare $\nu(x, y)$ to the sampling distribution for $\nu$ computed in the limit that the data contains no sources. This distribution is Gaussian with mean zero and width $\sqrt{2\pi\sigma^2 B}$ (Damiani et al. 1996). Because we do not know $B$ a priori, we use an iterative method by which we cleanse the data of suspected sources and derive the source-free Gaussian differential distribution, which provides a global estimate of $B$ across the instrument FOV. (Hence this method is less sensitive than methods that determine the background at each pixel; e.g., Damiani et al. 1996; Freeman et al. 1996) We fit a Gaussian model to the core of the distribution, and extrapolate it to determine the value $\nu_{\text{cut}}$ where the differential distribution exceeds the model by some factor (e.g., 3). We remove all data from pixels with $\nu > \nu_{\text{cut}}$, and re-iterate the procedure of correlating and fitting until no more suspected sources are found (this process converges—i.e., no new sources are found—after $\approx 4$ iterations). A multiple $m_0$ of the width of the final source-free Gaussian distribution, specifies the threshold cutoff for source detection, $\nu_0$, which we then compare to the first correlation map.
3. Application to \textit{ROSAT} PSPC Data

We apply our method to data of the \textit{ROSAT} PSPC. We note that the exposure is not constant across the PSPC FOV. Simulations of exposure-weighted background data show that there are more pixels in the wings of the source-free differential distribution than predicted by the Gaussian model. Cleansing those pixels causing the deviation can increase the derived width of this distribution and hence $\nu_0$; we limit our use of the method to where the total number of pixels involved in the deviation is small. For $B \sim 1 \text{ ct pix}^{-1}$, we use $\sigma = 2$, 4, and 8 pix; we do not use $\sigma < 2 \text{ pix}$ because of FFT aliasing. Also, the deviation means that we cannot analytically determine $m_0$ using the properties of the Gaussian distribution. We use simulations, and a criterion limiting the number of false X-ray sources to one per image, to determine that $m_0 = 5.6$, 4.5, and 4.1 for $\sigma = 2$, 4, and 8 pix, respectively.

We simulate exposure-weighted background to which we add one source, to determine the detection efficiency of our method. We calculate efficiencies at six locations on the \textit{ROSAT} PSPC image plane (Figure 3). At each location, we use the value of the instrumental broadening $\sigma_{\text{PSF}}$ to select an appropriate value of $\sigma$. We compare our results against those derived using a $S/N > 3$ detection criterion. We compute $S/N$ by simultaneously determining the source and background counts (cf. Harnden et al. 1984; Kashyap et al. 1994). In the center of the FOV, our method is considerably more sensitive than the $S/N$ method. The relative loss in sensitivity of our method near the edge of the FOV is due to the effect of exposure on the background count rate. More sophisticated treatments (e.g., Damiani et al. 1996; Freeman et al. 1996) have improved source-detection ability at the edge of the FOV.

Finally, we apply our method to a 31.7 ks observation of the Pleiades Cluster by the \textit{ROSAT} PSPC, in which $B \approx 0.94 \text{ cts pix}^{-1}$ (Micela et al. 1996). Micela et al. find 102 sources (of 214 optically-catalogued sources) at $S/N > 3$ within the
Figure 3. A comparison of the detection efficiencies of our technique (solid line) versus a criterion $S/N > 3$ criterion (dashed-dotted line), at six positions on the ROSAT PSPC image plane, for $B = 1$ ct pix$^{-1}$.

FOV. Our method finds 136, 96, and 54 correlation maxima above the threshold cutoff for $\sigma = 2$, 4, and 8 pix respectively. However, $\approx 20$ pairs of maxima for $\sigma = 2$ pix lie too close together to be considered independent sources, and are rather probably the result of Poisson fluctuations within one instrumentally-broadened source. Examining the combined results, we estimate $\approx 130$ sources in the FOV, or $\approx 30$ more than found with $S/N$ methods.

Acknowledgments. The authors thank the AXAF Science Center.

References

Damiani, F., Maggio, A., Micela, G., & Sciortino, S. 1996, this volume
Harnden, F. R., Jr., Fabricant, D. G., Harris, D. E., & Schwarz, J. 1984, SAO Special Report 393