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Image Processing Application for Cognition (IPAC) - Traditional and Emerging Topics in Image Processing in Astronomy

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Abstract. A new application framework for advanced image processing for astronomy is presented. It implements standard two-dimensional operators, and recent developments in the field of non-astronomical image processing (IP), as well as original algorithms based on nonlinear partial differential equations (PDE). These algorithms are especially well suited for multi-scale astronomical images since they increase signal to noise ratio without smearing localized and diffuse objects. The visualization component is based on the extensive tools that we developed for Spitzer Space Telescope's observation planning tool Spot and archive retrieval tool Leopard. It contains many common features, combines images in new and unique ways and interfaces with many astronomy data archives. Both interactive and batch mode processing are incorporated. In the interactive mode, the user can set up simple processing pipelines, and monitor and visualize the resulting images from each step of the processing stream. The system is platform-independent and has an open architecture that allows extensibility by addition of plug-ins. This presentation addresses astronomical applications of traditional topics of IP (image enhancement, image segmentation) as well as emerging new topics like automated image quality assessment (QA) and feature extraction, which have potential for shaping future developments in the field. Our application framework embodies a novel synergistic approach based on integration of image processing, image visualization and image QA (iQA).

1. Introduction

During the last twenty years the image processing (IP) community outside of astronomy has made substantial progress in developing powerful methods for IP and computer vision (Bovik 2005) which for the most part have not yet been utilized by the astronomy community. Adapting these advances for astronomy, and especially designing and implementing of an advanced image processing system which would utilize these continuing achievements, remains, however, a major challenge. The keystone elements of such a system which unifies a wide range of methods should be computational and visualization modules. Developers and users alike have realized that there is more to creating an extensible application than simple programming, and the objective is achieved here by exploiting the object oriented paradigm.

Astronomical data sets are increasing rapidly in size. Supporting interactive or semi-automated processing of vast data sets demands a new approach based on integration of image processing, visualization and iQA. This paper describes such a synergistic approach.

2. Image Enhancement as Pre-processing

Image enhancement is an important precursor to image segmentation (object detection), for either human interactive analysis, or for automatic processing. Astronomical images usually contain many point sources and, at the same time, extended diffuse structures. Often point sources are imbedded in diffuse structures. Noise reduction is one of the steps necessary for point source extraction and morphological studies. Applying traditional smoothing methods such as convolution with a Gaussian will inevitably erase small-scale objects. Moreover, for morphological studies of galaxy distribution, smoothing on scales larger than the scale at which the galaxy clustering correlation length is significant produces a Gaussian distribution by virtue of the central limit theorem (Coles & Lucchin 1995; Martinez et al. 2005, 2007). Overall, even though such an approach is effective at removing noise, it also has the unwanted side-effect of eliminating tiny objects, smearing more prominent ones, and blurring boundaries of extended structures.

There are two main approaches to the problem of smearing: wavelets (Stark et al. 1998, 2002; Martinez et al. 2005, 2007) and methods based on PDEs (Sapiro 2001, Bovik 2005; Pesenson et al. 2004, 2005, 2006; Lenzen et al. 2004). The framework presented here is based on nonlinear PDEs and one of them, the nonlinear diffusion (NLD) equation, will be discussed in the next section. It should be mentioned that the trade-off between smoothing and preserving objects is inevitable, and a balance between these two desirable, but conflicting objectives depends on the specific task.

2.1. Multi-scale representation of images by using PDEs

The aforementioned convolution of an image with a Gaussian is equivalent to solving a Cauchy problem for the linear PDE of diffusion with the noisy image as an initial condition. This explains the blurring of boundaries, as one would expect from diffusion. This insight has led to the construction of multi-scale representations of image data.

Multi-scale representations of image data are obtained by embedding a given image into a one-parameter family of derived images. This family should be parameterized by a scale parameter and be generated in such a way that fine-scale structures are successively suppressed when the scale parameter is increased. Such construction allows obtaining a separation of the image structures in the original image, such that fine scale image structures only exist at the finest scales in the multi-scale representation, thus simplifying the task of object detection. This objective can be achieved by employing the aforementioned connection between image processing and partial differential equations. Starting with a work of Perona & Malik (1987), filtering based on nonlinear PDEs has become very useful in image enhancement, image segmentation and edge detection. This state-of-the-art approach is based on the design and analysis of PDEs. Perona and Malik proposed a nonlinear diffusion equation with the coefficient of diffusion D decreasing when the gradient grows and increasing when the gradient decays

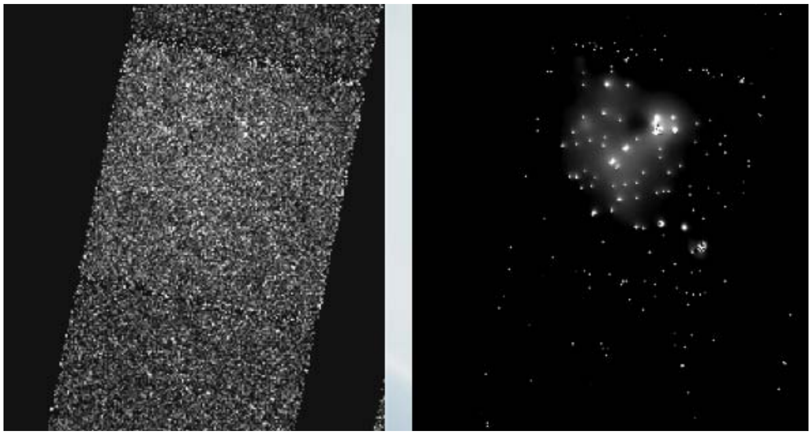

Figure 1. Left: the supernova remnant W28 (Chandra X-ray Observatory; courtesy of J. Rho (SSC, Caltech)). Right: same image after processing by a nonlinear diffusion equation.

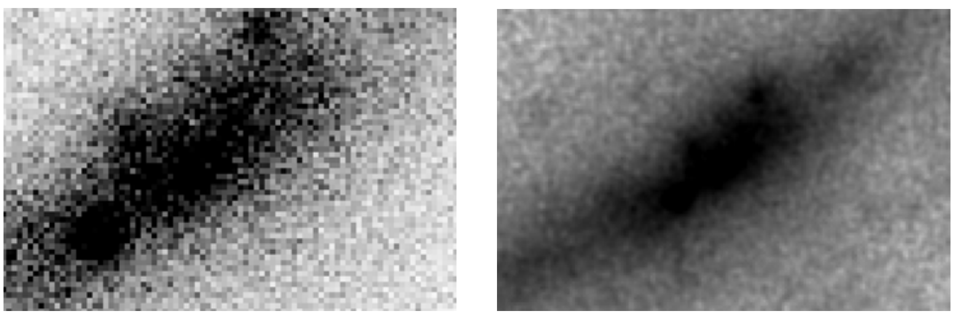

Figure 2. Left: NGC 2775 (Laine et al. 2007). Right: same image convolved with a Gaussian (kernel radius =2); color inverted.

$$u_t = div\left(D\left(\|\nabla u\|^2\right)\nabla u\right) \tag{1}$$

With the initial condition $u\,(t=0) = u_0$, and the coefficient of diffusion $D\left(\|\nabla u\|^2\right) = exp\left(-\|\nabla u\|^2 k^{-2}\right)$. Here $u_0(x,y)$ is the raw image and $u(t,x,y)$ is the evolved image at the time t. The parameter k characterizes the gradient scale of the initial image and controls the smoothing scheme. There is no optimal value for k and its magnitude depends on the task. It is important to know when to stop smoothing, but without a quantitative criterion, it becomes a very subjective task. Indeed, the original image is repeatedly smoothed as the number of iterations increases. To resolve this problem, Pesenson et al. (2005) introduced the reaction term $\beta(u-u_0)$ into the nonlinear diffusion equation. Here parameter β characterizes the noise level and is determined from uncertainties associated with each pixel. The reaction term prevents deviation of the smoothed image from the original one by more than the estimated noise. Another modification introduced in that work was the variable characteristic scale k which was recalculated after an a priori specified number of iterations.

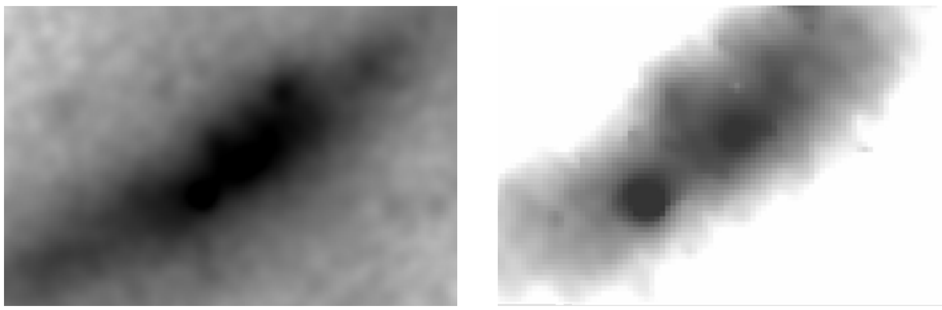

Figure 3. Left: NGC 2775 convolved with a Gaussian (kernel radius =5). Right: NGC 2775 processed by NLD (color inverted).

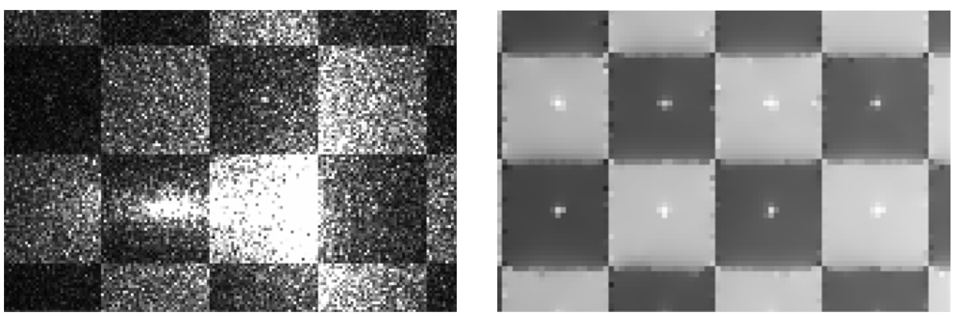

Figure 4. Left: simulated noisy image of a chessboard with localized objects at the center of each square. Right: same image processed by NLD; noise level has been reduced while the boundaries remain sharp and localized objects recovered.

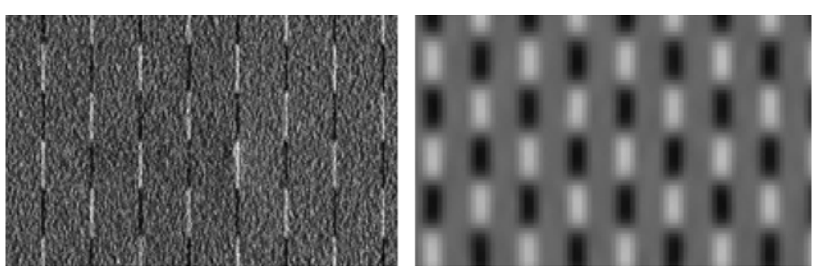

Figure 5. Left: detecting vertical boundaries directly from the simulated noisy image (Figure 4, left). Right: detecting vertical boundaries after convolving the noisy image with a Gaussian.

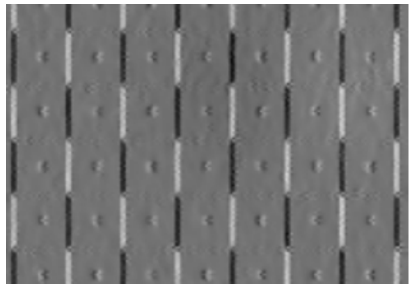

Figure 6. Detecting vertical lines from the noisy image preprocessed by NLD (Figure 4, right); compare this image with Figure 5.

Some examples of filtering based on the nonlinear diffusion equation (1) are given in Figures 1, 3, 4. Figure 4, right, clearly demonstrates how nonlinear diffusion stops at the boundaries, while the inner areas are all "cleaned up", and the localized objects at the centers of the squares have all been recovered.

3. Morphology Unveiling

Our framework also incorporates operators like shape detectors, texture analysis, edge detectors, etc.. Here we will discuss some of them, e.g. Sobel, Prewitt and Laplacian of Gaussian (LoG) which are used in image processing for detecting edges of objects in images (Bovik 2005). Artifacts in astronomical images often have sharp edges, so these operators, combined with shape detectors, facilitate detection of such artifacts (section 4). The Sobel and Prewitt methods of edge detection are basically different approaches to estimation of the gradient with the aid of convolution masks. The Prewitt masks give the weights for the best-fitting plane approximating the intensity in a 3x3 neighborhood, assuming all nine samples have equal weight. Comparing LoG and a high-pass filtering, on the one hand, with the Sobel and Prewitt operators on the other, demonstrates that the former group of methods is more sensitive to Gaussian type blobs and sharp edges, while the latter one is more sensitive to diffuse structures. Revealing morphology by using the latter group of operators is very effective and brings out complex structures which are not obvious in the original image. Ridges are just one example of such features, and indeed, one immediately gets the locus of the bow shock wave-front in Figures 7, 8. Thus this new way of looking at astronomical images facilitates morphology studies. This is why "Morphology Unveiling Operators" is a more accurate term for astronomical images than "Edge Detectors" as they are called in IP. Moreover, besides revealing complicated morphology, these operators at the same time bring out many faint point sources (Figure 7). This is because the gradient of a faint point source may be comparable with the gradient of a bright one, even if their fluxes are drastically different. This capability opens new possibilities for extracting point sources by thresholding in the gradient plane, rather than flux plane as it is usually done.

Since differentiation and convolution are linear operators, LoG is basically a Laplacian of an image which has been convolved with a Gaussian. Our framework enables one to create a new way of tackling the problem by creating a module flow (section 5, Figure 13) which is a sequence of the NLD module, and

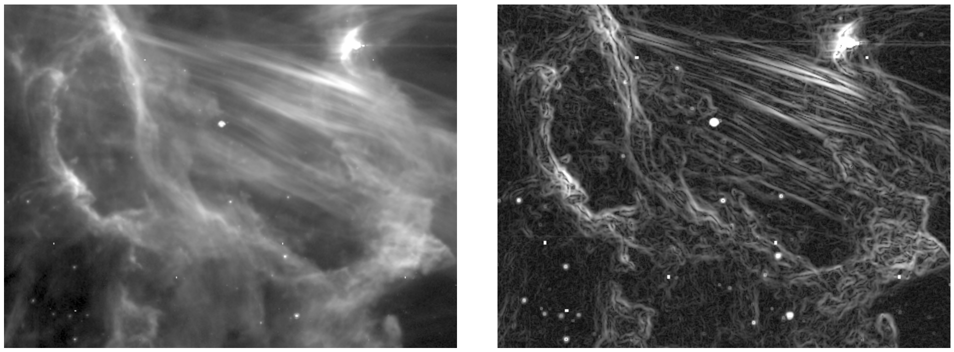

Figure 7. Left: IC 405, *Spitzer*, IRAC 8.0 μm (France et al. 2007). Right: same image, the gradient of flux. This new way of looking at astronomical images unveils fine structure and brings out embedded sources.

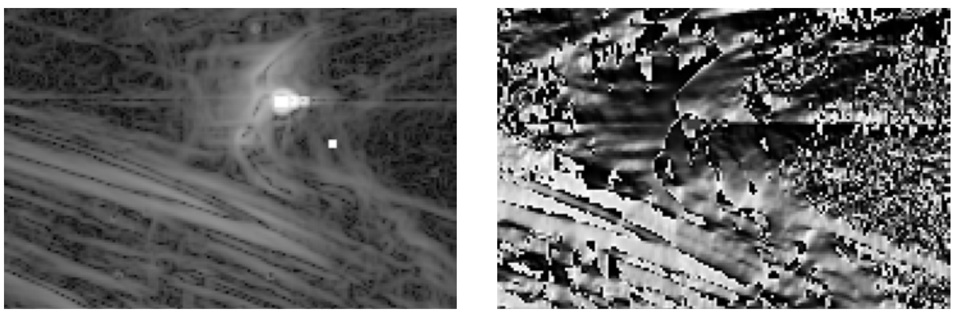

Figure 8. IC 405, *Spitzer*, IRAC 8.0 μm; the bow shock near HD 34078. Left: the gradient of flux. Right: the angle of the gradient of flux.

the Laplacian. It is thus becoming a new operator - the Laplacian of a nonlinear diffusion (LNLD). As we have demonstrated above, NLD equation preserves objects better than the convolution with a Gaussian, so LNLD is better suited for locating objects with relatively sharp boundaries. This can potentially be useful for automated image registration (Hack 2007).

All these operators are complementary to each other and may be used in different combinations with different settings (Figures 11 and 13) depending on the objective. The framework presented here allows one to create interchangeable sequences of operators (called flows; see section 5, Figure 13), thus facilitating various flexible combinations of different processing operators.

There are many important applications of the methods described in the last two sections since they facilitate interactive analysis and, more importantly, prepare grounds for automated extraction of different features.

4. Detection of Artifacts and Automated Image Quality Asessment

Simply implementing even the most powerful image processing algorithms is not sufficient because the ultimate goal of IP is better images, but "better" has no universal quantitative definition and depends on the task. Objective quality metrics consistent with subjective human evaluation should be devised, so that

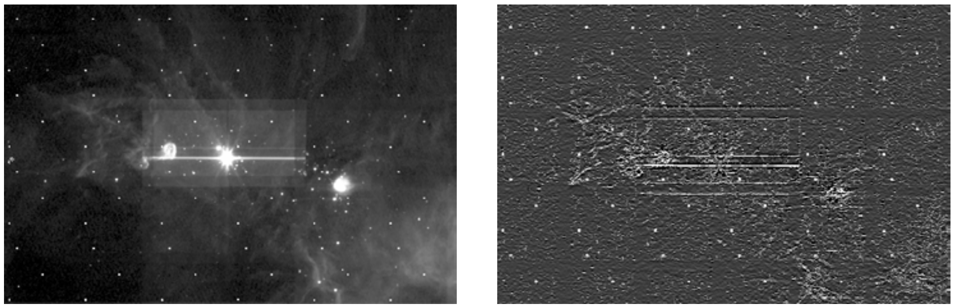

Figure 9. Left: mosaic of NGC 2264, *Spitzer*, IRAC, 8μm. Right: same mosaic after processing by NLD followed by our shape detector module to detect straight-line artifacts. In addition to bright lines, a faint grid pattern is now discernible (information about this grid is provided by the Spitzer Science Center together with the mosaic). Such processing can be used for quick QA screening and flagging "suspicious" images.

automated iQA can become a part of IP frameworks to monitor and evaluate quality of the processed images and dynamically optimize processing modules.

Moreover, since astronomical data volumes are increasing rapidly it is clear that manual monitoring of image QA for such sets will fail to serve. Indeed, the LSST alone will be producing about 30 TB of data per night, so automated QA in general and automated iQA in particular are crucial (Tyson 2007). However, to the best of our knowledge, existing approaches in astronomy to iQA (not to be confused with the calibration quality assessment) have not even begun to address the complete scope of the problem.

Traditional iQA metrics are basically variations of a simple mathematical measure called the mean squared error (MSE). MSE based measures, while very sensitive to trivial global image modifications, are insensitive to small details that might be of interest. Moreover, MSE measures make no distinction between noise and blur (and distortions in general) since they are based on an implicit assumption that image quality is independent of a spatial relationship between image samples. However, artifacts in astronomical images are often "structured" (artificial patterns, lines, signal-dependent noise), so an approach which does not take into account this structural information is not adequate. Our framework implements modules capable of automated detection of some artificial structures (just a few examples are given in this paper - Figures 6, 9, 10), thus enabling semi-automated image quality assessment.

Supporting interactive and semi-automated processing of vast data sets demands a new approach based on integration of image processing, analysis and iQA. The framework presented here is a first implementation of such a synergistic advance.

5. Cheetah - Visualization Tool and Pipeline Engine

Our application framework provides an integrated environment for processing astronomical images and has a very intuitive graphical user interface (GUI). It is built from libraries and reusable components developed for Spitzer Space Telescope's observation planning tool Spot and archive retrieval tool Leopard

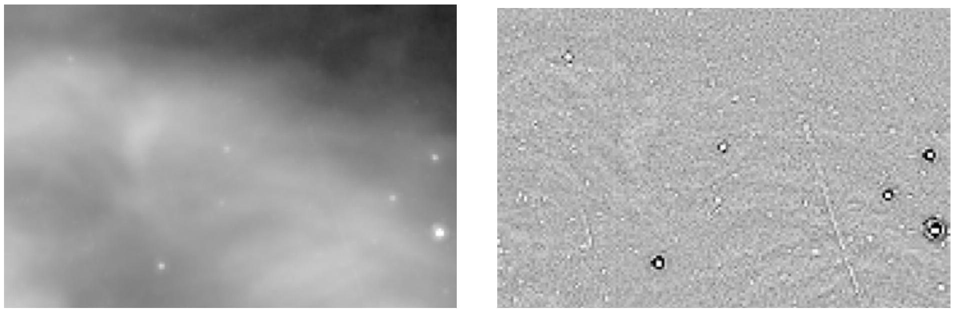

Figure 10. Left: an image of HH 34 (*Spitzer*, IRAC, 8μm, A. Noriega-Crespo). Right: Laplacian of a Gaussian applied to same image detects rad-hits which are not obvious in the original image.

(Roby et al. 2000), and as Leopard's successor is called Cheetah. Thus many components of Cheetah have already been well tested, so it is very mature, even though a new application. Cheetah allows the user to set up a pipeline interactively and to run images through it. The user can look at the final product or review the results of each step. The pipeline engine allows the user to rewind, tweak parameters (Settings; Figure 11, 13), and run the pipeline again from that point. This way the user can interactively fine-tune the pipeline to get the desired results. While the pipeline can be set up with a flow of processes, the user can also run any single process on the data without having to set up a pipeline.

One of the most exciting aspects of the Cheetah pipeline is its extensibility. The pipeline can be extended to any external program that takes a FITS file for input. The user can create a property file that defines the input, output, and parameters and then drop it into the cheetah pipeline directory.

Cheetah's image display capabilities open the door for the astronomer to creatively study his data. A user may overlay one or more images on top of the original image using transparency. This allows the user to see through his top layer into the bottom to study events that may appear in both data sets. He may also do three-color plots of his data (Figures 11(right) and 12) and then overlay another image transparently over this plot. By using combinations of this type of plotting, a user could potentially study six or seven data sets together at once. Each image has its display setting individually modified. This feature facilitates visualization of complicated structures.

Network access is another strength of the application. Cheetah accesses many of the common astronomy catalogs, images, and name resolution services available on the Internet for both fixed and moving targets. We are also adding VO client features in Cheetah.

6. Conclusion and Future Work

A new tool for processing astronomical images has been presented. It is a platform independent, open architecture application framework which is based on modern developments in the field of image processing. These denoising algorithms increase signal to noise ratio without smearing localized and diffuse ob-

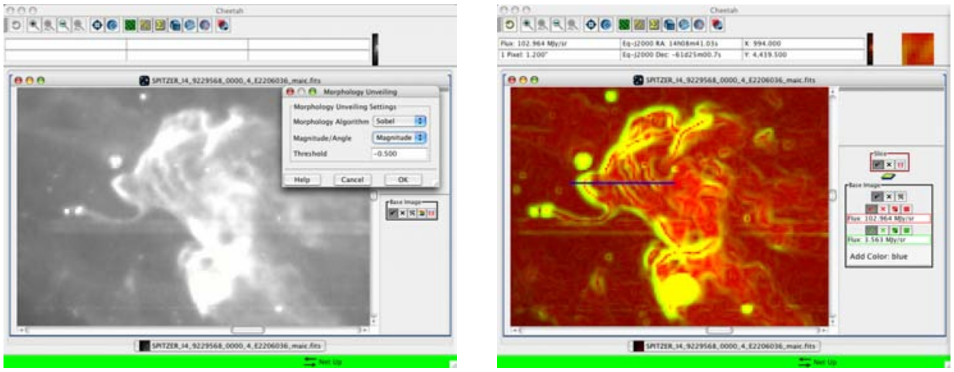

Figure 11. Screenshots from the framework. Left: choosing Southern Jellyfish Nebulae (*Spitzer*, IRAC 8.0 μm, Mercer et al. (2007)) to be processed; Settings dialog. Right: Pre- and post-processed (gradient of flux) images overlaid in different colors.

Figure 12. Flux cut of Figure 11(right); the blue (darker) curve is the processed image; note that there are different scales on the left and right vertical axis).

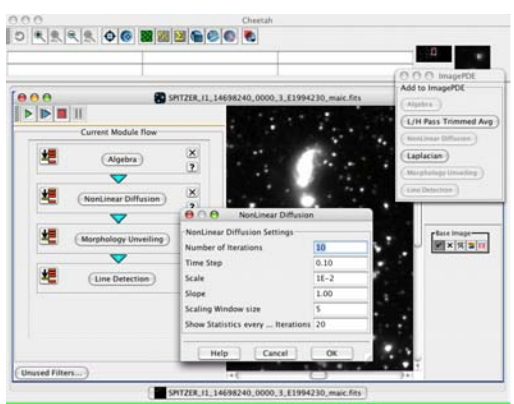

Figure 13. A screenshot from the framework. Creating a flow - a sequence of four different modules to the left of the image to be processed. In the middle is the Settings dialog for NLD module.

jects. The framework integrates image processing, image visualization and automated image quality assessment. Future developments include ability to read very large fits files with small memory footprint, application of the introduced methods to the analysis of long-slit spectra, incorporating frequency domain methods (Fourier analysis, wavelets), image classification based on automated extraction of objects of different shape and developing objective image quality metrics consistent with subjective human evaluation of astronomical images.

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