*Astronomical Data Analysis Software and Systems XX*
*ASP Conference Series, Vol. 442*
*Ian N. Evans, Alberto Accomazzi, Douglas J. Mink, and Arnold H. Rots, eds.*


# EMphot — Photometric Software with Bayesian Priors: Application to GALEX

Simon Conseil,[1] Didier Vibert,[1] Stéphane Arnouts,[2] Bruno Milliard,[1] Michel Zamojski,[3] Antoine Llebaria,[1] and Mireille Guillaume[4]

[1]*Laboratoire d'Astrophysique de Marseille, OAMP, Université Aix-Marseille & CNRS, Marseille, France*

[2]*Canada France Hawaii Telescope, Kamuela, Hawaii, United States*

[3]*California Institute of Technology, Pasadena, United States*

[4]*Institut Fresnel, Université Aix-Marseille, Marseille, France*

**Abstract.** EMphot is a software tool for the photometry of astrophysical sources, galaxies and stars, in crowded field images. Its goal is to estimate the flux in a low resolution band using prior information (position and shape) from a better resolved band, in a Bayesian approach under the Poisson noise assumption. The solution is reached with an Expectation-Maximization (EM) algorithm for solving the photometry and includes several steps: prior shapes deblending in high resolution images, astrometry correction, PSF optimization, background correction from the residual.

## 1. Introduction

Photometry of astrophysical sources, galaxies and stars, in crowded field images, if an old problem, is still a challenging goal, with current and future survey missions releasing new data with increased sensitivity, resolution and field of view.

This paper gives an overview of EMphot, details on the different components can be found in several papers from the same team: Guillaume et al. (2006) present the original procedure used to face on this challenge, using the Poisson statistics to define the Bayes assumption and solve for the maximum posterior likelihood with the constraint for all fluxes to be positive. Llebaria et al. (2008) discuss the photometric performance and behavior of the method when dealing with imperfect knowledge of background, PSF and object positions. Vibert et al. (2009) describe the improvement of using the extended shape inferred by deblending the high resolution optical images and not only the position of the optical sources.

## 2. Maximum Likelihood Parametric Estimation with Priors: Expectation-Maximization (EM)

The specificity of the proposed photometric procedure is the Bayesian approach under the Poisson noise assumption. The solution is reached with an EM algorithm.

Let be $x_i$ for $i \in \{1, ...M\}$ the observed value on pixel $i$ of the UV image considered as a sample of the random variable $X_i$ following a Poisson statistics. Let be $\mu_i = E\{X_i\}$ for $i \in \{1, ...M\}$ the expected values for this image. Let be $h_{k,i}$ the known relative value of object $k \in \{1, ...K\}$ on pixel $i$ deduced from the visible catalog. Let be $\alpha^T = (\alpha_1, \dots \alpha_k)$ the vector of unknown fluxes of these objects. Let be $r_i$ the relative instrument response taking into account exposure time and efficacy of the system. Last, let $b_i$ be the known background level value on pixel $i$ of the UV image. We define the model for the UV image as follows:

$$\forall i \in \{1, \dots M\} \begin{cases} \mu_i = r_i \sum_{k=1}^{K} \alpha_k h_{k,i} + r_i b_i \\ P\{X_i = x_i\} = \exp(-\mu_i)\frac{\mu_i^{x_i}}{x_i!} \end{cases} \quad \text{where} \quad h_{k,i} = \sum_j o_{k,j} f_{i-j} \tag{1}$$

here $h_{k,i}$ results from the convolution between each object known profile $o_{k,i}$ with the point spread function $f_i$ of the imaging system. By normalizing the function $h_{k,i}$ to unity, this model allows to estimate directly $\alpha$, the flux vector of the set of sources in the image. As was shown in more detail in (Guillaume et al. 2006), introducing the expectation maximization scheme, we get the iterative algorithm:

$$\alpha_k^{(n+1)} = \alpha_k^{(n)} \frac{\sum_{i=1}^{M} \frac{x_i}{\mu_i^{(n)}} r_i h_{k,i}}{\sum_{i=1}^{M} r_i h_{k,i}} \quad \text{where} \quad \mu_i^{(n)} = r_i \sum_{j=1}^{K} \alpha_j^{(n)} h_{j,i} + r_i b_i \tag{2}$$

The E step compares the data image $x_i$ to the projection $\mu_i^{(n)}$ of the $\alpha_i^{(n)}$ estimates. The result is introduced in the M step as the corrective ratio needed for the new set of $\alpha_k^{(n+1)}$ estimates. The background level $b$ is considered known, we found it in a previous procedure.

## 3. Features

- **Prior shapes computation:** Firstly, a deblending is done using SExtractor ellipses to define objects contour. Central symmetry is used to determine the flux assigned to each object blended in one pixel. Secondly, the image is degraded to the resolution of the GALEX image.
- **Astrometry correction:** cross-correlate the positions of the brightest objects (detected with SExtractor) with the brightest objects of the prior catalog and warp with a $2^{nd}$ order polynomial fitting.
- **Image processed by tiles**.
- **Initial fluxes** $\alpha_i^{(0)}$: use U-band value or estimate from the image using a PSF weighted sum.
- **Prior flux constraint:** $\text{mag}_{UV} > \text{mag}_U - 1$
- **PSF rescaling:** we optimally rescale the PSF maximizing the likelihood with respect to the PSF scale for known fluxes.
- **Error estimation** from the residual: $\widehat{\sigma}_k^2 = \sum_{i=1}^{M} h_{k,i}(x_i - \widehat{\mu}_i)^2 / \sum_{i=1}^{M} h_{k,i}^2$
- **Background correction:** mask and do the inpainting around objects artifacts in the residual, filter high frequencies and redo EM iterations.
- **Post-processing** of the output catalog: flag objects inside GALEX and CFHTLS masks, compute statistics on nearest neighbors, compare with GALEX catalog.

## 4. Simulations

The resulting photometric accuracy is quantified with both completely simulated crowded fields and simulated objects added on top of the real images. Error estimation is done using Monte-Carlo simulations, adding simulated objects to the real image or simulating all the objects, using the number counts from GALEX. Simulations use astrometry corrections, stamps or an optimal PSF scale value to be consistent with the processing algorithm.

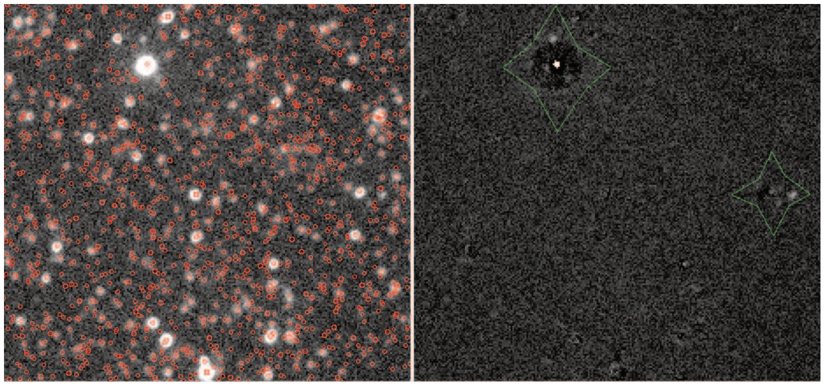

Figure 1. XMMLSS_00 NUV field with 200 iterations, left: GALEX image (priors in red), right: EM residual (masked region in green).

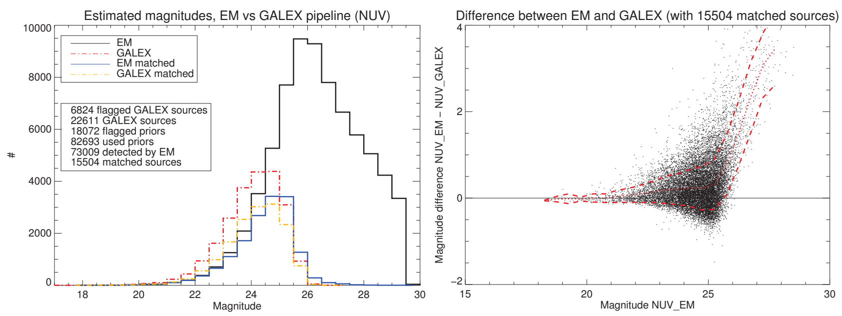


Figure 2. Comparison SExtractor / EMphot.

## 5. Results

We apply this software to the Deep Imaging Survey (DIS) of the GALEX mission, which observes in two UV bands with long exposure times ($\sim 70,000$s), and produces deep sky images of 1 square degree, with hundreds of thousands of galaxies or stars. Priors are computed from CFHTLS data. These UV observations are of lower resolution than same field observed in visible bands, and with a very faint signal dominated by the photon shot noise, with background level around 100 (resp. 10) counts in the near (resp. far) UV band. Figures 1, 2 and 3 show the results on XMMLSS_00 NUV field.

## 6. Conclusion

Finally, compared to blind photometry estimation, the method leads to small and flat residuals, increases the faint source detection threshold, and provides a better accuracy for bright contaminated objects. On the processed DIS fields, EM provides good photometry and completeness down to magnitude 25.5, which is 1 magnitude deeper than the GALEX pipeline. As an important by-product, the method automatically solves the problem of determining the optical counterparts to UV sources, and shares the UV flux between partly resolved or unresolved nearby objects. The method is also an optimal approach for measuring drop-outs in FUV and NUV.

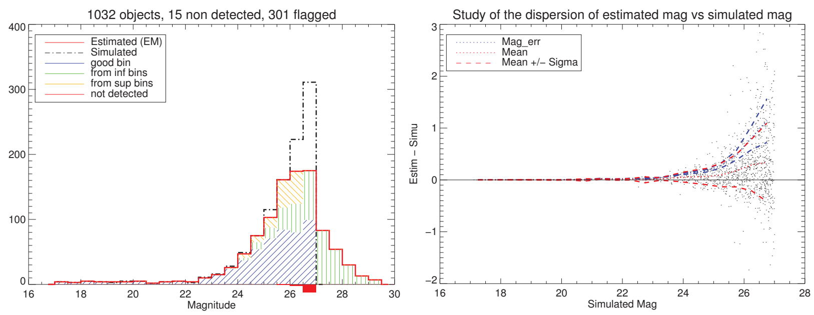


Figure 3. Monte-Carlo simulations on XMMLSS_00 NUV with $3 \times 500$ objects added to the image.

Future developments involve PSF parametrization, Gaussian noise (BVLS), application to HERSCHEL, Model selection method for reducing prior number and Astrometry improvement with a maximum-likelihood recentering.

## References

Guillaume, M., Llebaria, A., Aymeric, D., Arnouts, S., & Milliard, B. 2006, in Image Processing: Algorithms and Systems, Neural Networks, and Machine Learning, edited by E. R. Dougherty, J. T. Astola, K. O. Egiazarian, N. M. Nasrabadi, & S. A. Rizvi (Bellingham, WA: SPIE), vol. 6064 of Proc. SPIE, 332

Llebaria, A., Magnelli, B., Arnouts, S., Pollo, A., Milliard, B., & Guillaume, M. 2008, in Image Processing: Algorithms and Systems VI, edited by J. T. Astola, K. O. Egiazarian, & E. R. Dougherty (Bellingham, WA: SPIE), vol. 6812 of Proc. SPIE, 68121F

Vibert, D., Zamojski, M., Conseil, S., Llebaria, A., Arnouts, S., Milliard, B., & Guillaume, M. 2009, in Computational Imaging VII, edited by C. A. Bouman, E. L. Miller, & I. Pollak (Bellingham, WA: SPIE), vol. 7246 of Proc. SPIE, 72460U