

Introduction

In astronomical image acquisition, it is common to find artifacts and anomalies because the particularities of the studied objects (distance, light intensity, physical nature, etc.), as well as the acquisition process (instrumental aberrations, atmospheric turbulence, etc.). Two of these aberrations are the Poisson noise and the effect of the point spread function (PSF).

Poisson noise occurs due to the oscillatory nature of light measurements by optical captation instruments. The low number of photons that the instruments capture means that this noise can be modeled using a Poisson distribution. It has the particularity of being closely correlated with the real image. On the other hand, the PSF models the response of an optical captation system to an input in the form of a Dirac delta, and it generates a blurring effect and a loss of spatial resolution. In the case of shift-invariant systems, the resulting image can be approximated as the convolution of the real image with the PSF.

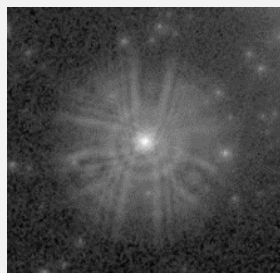


Figure 1: Image captured by Hubble Space Telescope affected by its point spread function (HubbleSite.org, n.d.)

Motivated for the recent advances in the field of Deep Learning for image reconstruction, we have built a solution based on convolutional neural network (CNN) for astronomic image aberrations removal.

Materials and Methods

We have built the model based on the framework described by Mao, Shen and Yang (2016) for the construction of CNNs specialised in image restoration, using architectures formed by auto-encoders and skip-connections. We have also based our model from the one proposed by Liu & Lam (2018) with a proven efficiency for the removal of Poisson noise in natural images (which is also based on the text of Mao et al.). The main features of our model are:

- **Auto-encoder** based architecture allows to **extract fundamental image features** by forcing the network to learn compressed representations of the image.
- Possibility to **recover lost features** in the compression phase through skip-connections.
- **Abolition of the gradient descent problem**, allowing the use of very deep networks.
- **Two branches specialised** in different tasks: **aberrations removal** and **image reconstruction**. This is due to their different compression ratios. The contribution of both branches allows the network to remove Poisson noise with minimal loss of detail in the reconstruction process.

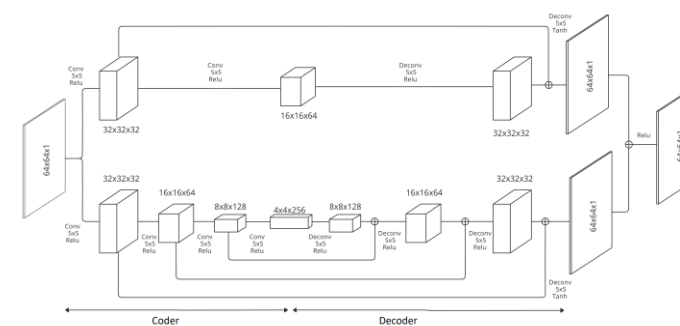


Figure 2: Our CNN model architecture inspired in Liu and Lam (2018) model

The required dataset to train and evaluate the model have been artificially generated using the GalSim software (Rowe et al., 2015). We generate a total of 8,100 galaxies affected by the aberrations and their respective ground truth, and we dedicate 70% of the datasets for training, 20% for validation and 10% for testing. As evaluation metrics, we use the peak signal to noise ratio (PSNR) and the structural similarity (SSIM)

Results

Here, we show the average results obtained training both Liu and Lam model and ours for the deconvolution problem. We observe high gains in both PSNR and SSIM in table 2, between 7 and 8 dB for PSNR and around 0.50 for SSIM.

Model	PSNR input image (dB)	PSNR output image (dB)	SSIM noised image	SSIM output image
Liu and Lam	32,08	39,75	0,424	0,930
Our Model		40,05		0,960

Table 1: Resulting metrics

In figure 3 we show a reconstruction example of a galaxy of our dataset. We observe that the Poisson noise is effectively removed and there is a good reconstruction of the galaxy core, showing an improvement of the overall spatial resolution. However, if we observe the same resulting images in logarithmic scale (in order

to highlight the lower intensities) we observe that there are point-like sources that cannot be recovered during the reconstruction process. We can also observe the loss of part of the halo.

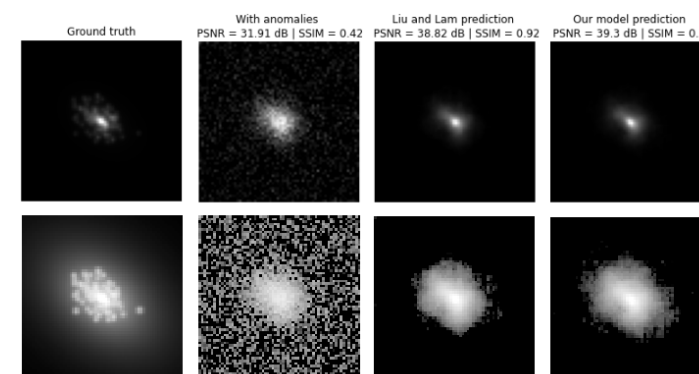


Figure 3: Examples of reconstructed images by both our model and Liu and Lam (2018) model trained for deconvolution. First row shows images in linear scale. Second are the same images above but

Conclusions

In view of the obtained results, we can conclude that our architecture performs well for Poisson denoising tasks. For the full deconvolution problem, we can increase the spatial resolution of the images, recovering the core and the main structure of the galaxy, with gains between 7 and 8 dB for PSNR and around 0.5 for SSIM. However, the model is not able to recover weaker structures associated with the halo and point-like objects. Although a good partial reconstruction of the galaxy is achieved, there is information of interest that is lost.

We would like to emphasise the simplicity of the chosen architecture. There are more powerful options, such as generative adversarial networks, that are currently trending topic in image reconstruction problems, which might obtain better results and demonstrate the full effectiveness of deep learning for the reconstruction of astronomical images.

Contact:

E-mail: javihdezafon@gmail.com

LinkedIn: www.linkedin.com/in/javierhernandezafonso

Literature cited

- 1.Beckouche, S., Starck, J. L., & Fadili, J. (2013). Astronomical image denoising using dictionary learning. *Astronomy & Astrophysics*, 556, A132.
- 2.News releases. HubbleSite.org. (n.d.). Retrieved 1994, from <http://hubblesite.org/newscenter/archive/releases/1994/05/image/c/>
- 3.Liu, P.-Y., & Lam, E. Y. (2018). *Image Reconstruction Using Deep Learning*. <https://arxiv.org/abs/1809.10410v1>
- 4.Mao, X.-J., Shen, C., & Yang, Y.-B. (2016). Image Restoration Using Very Deep Convolutional Encoder-Decoder Networks with Symmetric Skip Connections. *Advances in Neural Information Processing Systems*, 29. <https://bitbucket.org/chhshen/image-denoising/>
- 5.Rowe, B. T. P., Jarvis, M., Mandelbaum, R., Bernstein, G. M., Bosch, J., Simet, M., Meyers, J. E., Kacprzak, T., Nakajima, R., Zuntz, J., Miyatake, H., Dietrich, J. P., Armstrong, R., Melchior, P., & Gill, M. S. S. (2015). GalSim: The modular galaxy image simulation toolkit. *Astronomy and Computing*, 10, 121–150. <https://doi.org/10.1016/J.ASCOM.2015.02.002>