Astronomical Image Reconstruction with Convolutional Neural Networks

Rémi Flamary
Université Côte d'Azur
Lagrange, OCA, CNRS
Nice, France
Email: remi.flamary@unice.fr

Abstract—State of the art methods in astronomical image reconstruction rely on the resolution of a regularized or constrained optimization problem. Solving this problem can be computationally intensive and usually leads to a quadratic or at least superlinear complexity *w.r.t.* the number of pixels in the image. We investigate in this work the use of convolutional neural networks for image reconstruction in astronomy. With neural networks, the computationally intensive tasks is the training step, but the prediction step has a fixed complexity per pixel, *i.e.* a linear complexity. Numerical experiments show that our approach is both computationally efficient and competitive with other state of the art methods in addition to being interpretable.

I. INTRODUCTION

Astronomical image observation is plagued by the fact the the observed image is the result of a convolution between the observed object and what the astronomers call a Point Spread Function (PSF) [1] [2]. In addition to the convolution the image is also polluted by noise that is due to the low energy of the observed objects (photon noise) or to the sensor. The PSF is usually known *a priori*, thanks to a physical model for the telescope of estimation from known objects. State of the art approaches in astronomical image reconstruction aim at solving an optimization problem that encodes both a data fitting (with observation and PSF) and a regularization term that promote wanted properties in the images [1], [3], [4]. Still, solving a large optimization problem for each new image can be costly and might not be practical in the future. Indeed in the coming years several new generations of instruments such as the Square kilometer Array [5] will provide very large images (both in spatial and spectral dimensions) that will need to be processed efficiently.

The most successful image reconstruction approaches rely on convex optimization [3], [4], [6] and are all based on gradient [7] or proximal splitting gradient descent [8]. Interestingly those methods have typically a linear convergence, meaning that the number of iterations necessary to reach a given precision is proportional to the dimension n of the problem [9], where n is the number of pixels. Since each iteration is at best of complexity n (the whole image is updated), the overall complexity of the optimization is $O(n^2)$. Acceleration techniques such as the one proposed by Nesterov [10][9] manage to reduce this complexity to $O(n^{1+1/2})$ which is still superlinear *w.r.t.* the dimension of the image. This is

the main motivation for the use of neural networks since they lead to a linear complexity $O(n)$ that is much more tractable for large scale images.

Convolutional neural networks (CNN) have been widely used in machine learning and signal processing due to their impressive performances [11], [12], [13]. They are of particular interest in our case since the complexity of the prediction of a given pixel is fixed *a priori* by the architecture of the network, which implies a linear complexity for the whole image. They also have been investigated early for image reconstruction [14] and recent advances in deep learning have shown good reconstruction performances on natural image [15].

The purpose of this work is to investigate the feasibility and performances of CNN in astronomical image reconstruction. In the following we first design such a neural network and discuss its learning and implementation. Then we provide numerical experiments on real astronomical images with a comparison to other state of the art approaches followed by an interpretation of the learned model.

II. CONVOLUTIONAL NEURAL NETWORK FOR IMAGE RECONSTRUCTION

A. Network architecture

Neural network models rely on processing the input through several layers each consisting of a linear operator followed by a nonlinear transformation with an activation function [13]. Multi-layers and more recently deep neural nets allow for a more complex nonlinear model at the cost of a more difficult model estimation [13]. We choose in this work to use a 3-layer convolutional neural networks with Rectified Linear Unit activation (ReLU) as illustrated in Figure 1. We discuss in the remaining of this section the reasons for those choices.

As their name suggests, convolutional layers perform their linear operator as a convolution. They have been shown to work well on image reconstruction problems in [15] which is why we use them in our design. An interesting property is that the number of parameters of a layer depends only on the size of the convolution (the filter) and not the size of the input image. Also a convolution operator is common and can benefit from hardware acceleration if necessary (Cuda GPU, DSP). We used 64, 10×10 filters in the first layer in order to allow for more complex and varied filtering of the raw data to feed the higher order representations of the following
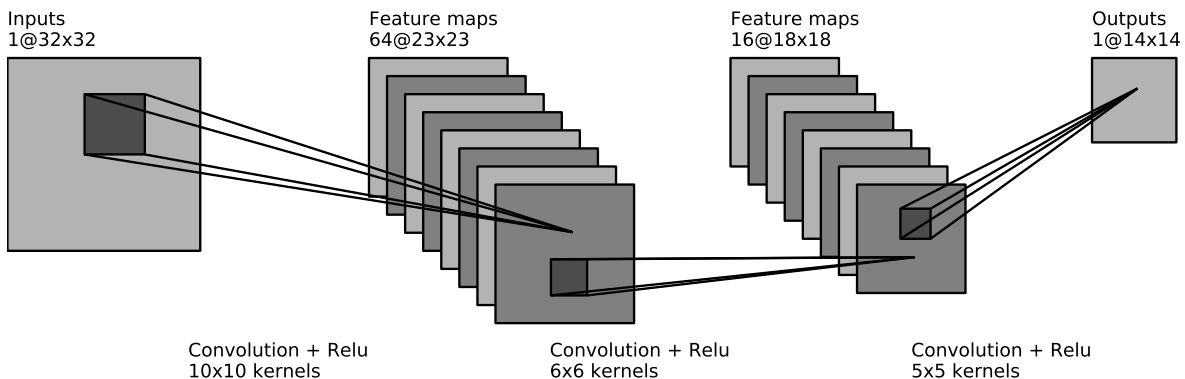
Fig. 1. Architecture of the proposed convolutional neural network. On the upper part are reported the size of the input, intermediary images and outputs. On the lower part the parameters and size of the filters for each layer.

layers. Note that at each layer the dimensionality of the image decreases because we want the convolution to be exact which implies a smaller output. In our model as shown in Figure 1, we have a 14×14 output for a 32×32 input image. From the multiple convolutions, we can see that the predicted value of a unique pixel is obtained from a 18×18 window in the input image. Finally this architecture has been designed for a relatively small PSF, and the size of the filters should obviously be adapted for large PSF.

Rectified Linear Units (ReLU) activation function has the form $f(x) = \max(0, x)$ at each layer [16]. ReLU is known for its ability to train efficiently deep networks without the need for pre-training [17]. One strength of ReLU is that it will naturally promote sparsity since all negative values will be set to zero [17]. Finally the maximum forces the output of each layer to be positive, which is an elegant way to enforce the positive physical prior in astronomical imaging.

B. Model estimation

The model described above has a number of parameters that have to be estimated. They consist of 64, 10×10 filters for the first layer, $64*16$, 6×6 for layer two and finally 16, 5×5 filters for the last layer that merges all the last feature maps. It is interesting to note that when compared to other reconstruction approaches, the optimization problem applies to the model training that only needs to be done once. We use Stochastic Gradient Descent (SGD) with minibatch to minimize the square Euclidean reconstruction loss. In practice it consists in updating the parameters using at each iteration the gradient computed only on a subset (the minibatch) of the training samples. This is a common approach that allows for very large training datasets and limits the effect of the highly non convex optimization problem [12]. Interestingly, minibatches are handled in two different ways in our application. Indeed we can see that for a given input in the model the gradient is computed for all the 14×14 output pixels, which can be seen as a local minibatch (using neighboring pixels). One can also use a minibatch that computes the gradient for several inputs that can come from different places in one image and

even from different images. This last approach is necessary in practice since it limits overfitting and helps decrease the variance of the gradient estimate [13].

Finally we discuss the training dataset. Due to the complexity of the model and the large number of parameters, a large dataset has to be available. We propose in this paper to use a similar approach as the one in [15]. Since we have a known model for the PSF, we can use clean astronomical images and generate convolved and noisy images used to generate the dataset. The input for a given sample is extracted from the convolved and noisy image while the output is extracted from the clean image. In the numerical experiments we extract a finite number of samples, whose positions are randomly drawn from several images. A large dataset drawn from several images will allow the deep neural network to learn the statistical and spatial properties of the images and to generalize it to unseen data (new image in our case).

C. Model implementation and parameters

The model implementation has been done using the Python toolboxes Keras+Theano that allow for a fast and scalable prototyping. They implement the use of GPU for learning the neural network (with SGD) and provide efficient compiled functions for predicting with the model. Learning a neural network requires to choose a number of parameters that we report here for research reproducibility. We set the learning rate (step of the gradient descent) to 0.01 with a momentum of 0.9 and we use a Nesterov-type acceleration [10]. The size of the minibatch discussed above is set to 50 and we limit the number of epochs (number of times the whole dataset is scanned) to 30. In addition we stop the learning if the generalization error on a validation dataset increases between two epochs. The training dataset contains $100,000$ samples and the validation dataset, also obtained from the training images, contains $50,000$ samples. Using a NVIDIA Titan X GPU, training on one epoch takes approximately 60 seconds.

III. Numerical experiments

In this section we first discuss the experimental setup and then report a numerical and visual comparison. Finally we illustrate the interpretability of our model. Note that all the code and estimated models will be available to the community on GitHub.com[1].

A. Experimental setting

We use in the experiment 6 astronomical images of well known objects obtained from the STScI Digitized Sky Survey, HST Phase 2 dataset[2]. The full images, illustrated in Figure 2, are 3500×3500 and represent a 60 arc minute aperture. Those images were too large for an extensive parameter validation of the methods so we used 1024×1024 images centered on the objects for the reconstruction comparison. The full images were used only for training the neural networks. All images have been normalized to have a maximum value of 1.0. They are then convolved by a PSF with circular symmetry corresponding to a circular aperture telescope also known as an Airy pattern of the form $PSF(r) = I_0 \left(J_1(r)/r \right)^2$ where r is a radius scaled to have a width at half maximum of 8 pixels in a 64×64 (see Figure 3 first row). Finally a Gaussian noise of standard deviation $\sigma = 0.01$ is added to the convolved image.

We compare our approach to a classical Laplacian-regularized Wiener filter (Wiener) [1, Sect. 3] and the iterative Richardson-Lucy algorithm (RL) [18], [19] that is commonly used in astronomy. We also compare to a more modern optimization based approach that aim at reconstructing the image using a Total Variation regularization [20] (Prox. TV). This last algorithm has been used with success in radio-astronomy with additional regularization terms [6]. This last approach is a proximal splitting method with a computational complexity equal to [3], [6]. In order to limit the computational time of the image reconstruction, Prox. TV was limited to 100 iterations. Finally, in order to evaluate the interest of using non-linearities in the layers of our neural network, we also investigated a simple 1-layer convolutional neural net (1-CNN) with a unique 18×18 linear filter (same window as the proposed 3-CNN model) and a linear activation function. Interestingly this last method can also be seen as a Wiener filtering whose components are estimated from the data.

In order to have a fair comparison we selected for all the state of the art methods the parameters that maximize the reconstruction performance on the target image. In order to evaluate the generalization capabilities of the neural networks, the networks are trained for each target image using samples from the 5 other images. In this configuration the prediction performance of the network is evaluated only on images that were not used for training.

B. Reconstruction comparisons

Numerical performances in Peak Signal to Noise Ratio (PSNR) are reported for all methods and images in Table I.

[1]GitHub repository: https://github.com/rflamary/AstroImageReconsCNN
[2]Dataset website: http://archive.stsci.edu/cgi-bin/dss_form
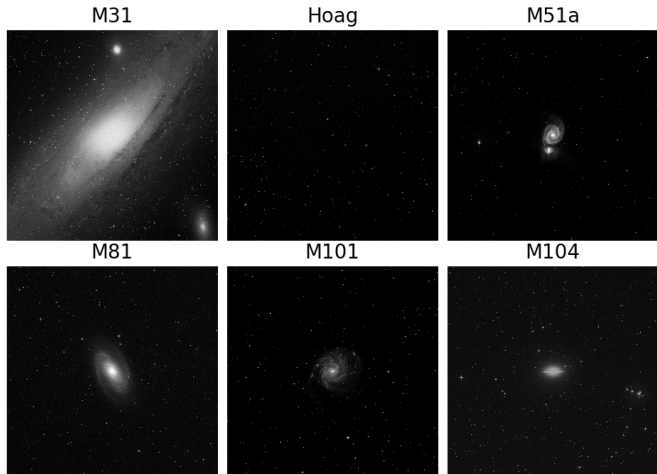
Fig. 2. Images used for reconstruction comparison.

Image	Wiener	RL	Prox. TV	1-CNN	3-CNN
M31	35.42	35.11	35.17	35.82	**36.03**
Hoag	37.29	37.99	36.66	38.58	**39.99**
M51a	38.07	38.26	37.68	38.96	**39.99**
M81	35.91	35.90	35.38	36.79	**37.26**
M101	36.66	37.79	35.87	38.31	**39.63**
M104	36.01	35.89	35.34	37.25	**38.10**
Avg PSNR	36.47	36.65	35.93	37.48	**38.23**
Avg time (s)	**0.24**	1.15	203.44	0.52	1.30

TABLE I

Peak Signal to noise ratio (dB) for all image reconstruction methods on all 6 astronomical images. We also report the average computational time in sec. of each methods

Note that our proposed 3-CNN neural network consistently outperforms other approaches while keeping a reasonable computational time ($\approx$ 1s for a 1024×1024 image on the machine used for the experiments). 1-CNN works surprisingly well probably because the large dataset allows for a robust estimation of the linear parameters. In terms of computational complexity, Wiener is obviously the fastest method followed by Richardson-Lucy that stops after few iterations in the presence of noise. Our approach is in practice very efficient compared to the optimization based approach Prox. TV. In this scenario Prox TV leads to limited performances suggesting the use of alternative regularizers such as Wavelets [3], [6] that we will investigate in the future. Still note that even if other prior could lead to better performances, the computational complexity will be the same. One of the major interest of our method here is that its complexity is linearly proportional to the number of pixel so that we can predict exactly the time it will take on a given image ($1.3 * 4 = 5.2s$ on a 2048×2048 image). Also since the network use a finite input window, it can be performed in parallel on different part of the image which allow a very large scaling on modern HPC or cloud.

Finally we also show a visual comparison of the different image reconstructions on a small part of the M51a image in Figure 3. Again we see that the 3-layer convolutional neural network leads to a more detailed reconstruction.
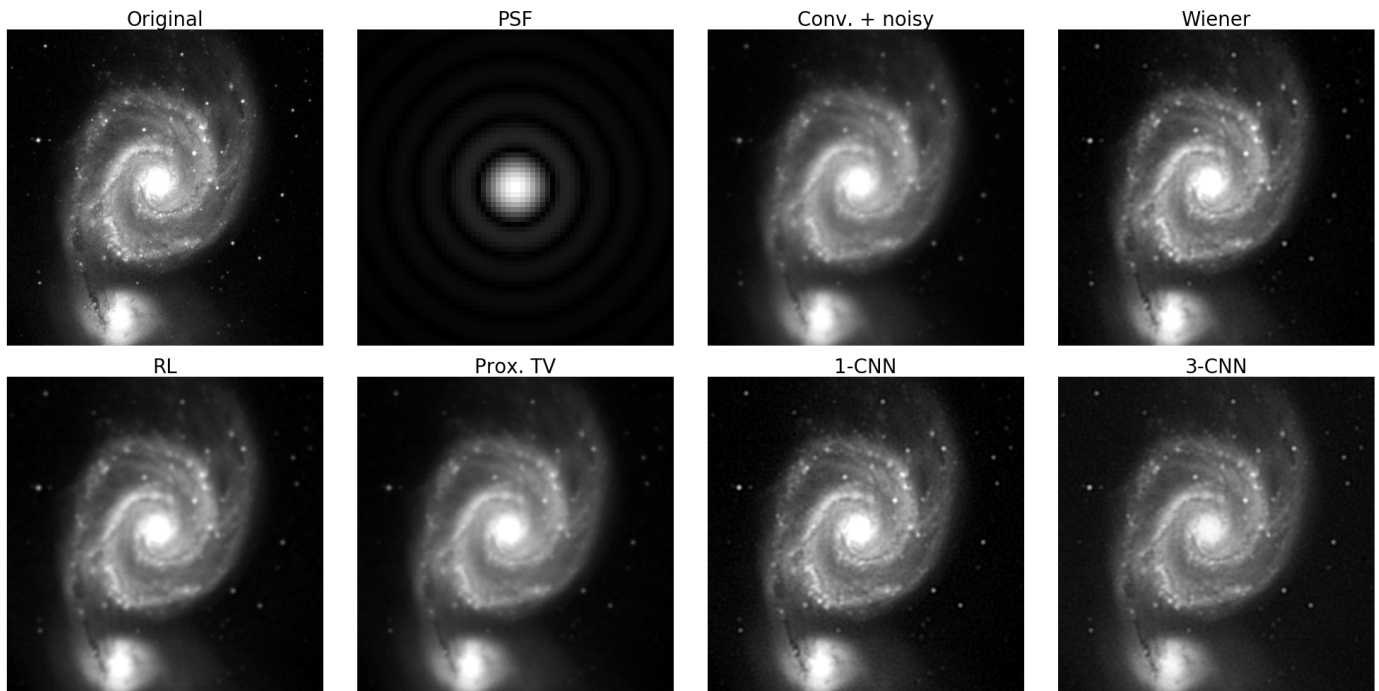
Fig. 3. Visual comparison of the reconstructed images for M51a. Note that the PSF image is zoomed and we show the square root of its magnitude for better illustration.
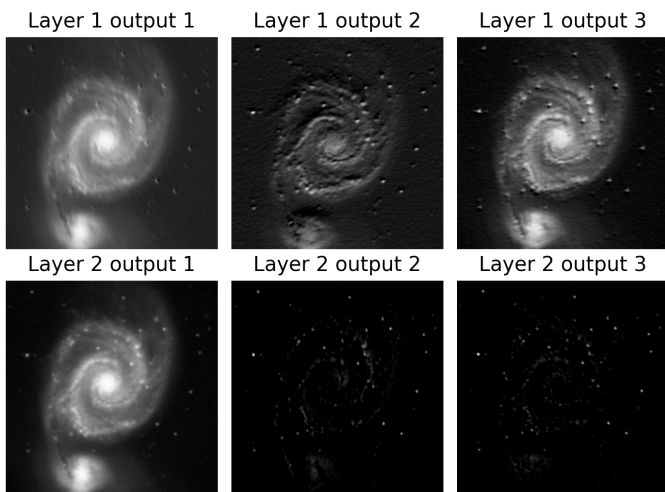

Fig. 4. Selection of intermediate feature maps in the first (top row) and second (bottom row) layer of the neural network.

C. Model interpretation

One of the strengths of CNN is that the feature map at each layer is an image that can be visualized. We report in Figure 4 a selection of features maps from the output of the first and second layers. We can see that the first layer contains some low pass or directional filtering whereas layer two contains more semantic information. In this case we can see in layer 2 an image that represents a smooth component describing the galaxy and a more high frequency component representing point sources of a star field. The source separation

was learned by the network using only data which is very interesting because it is a well known prior in astronomical images that have been enforced in [21].

IV. CONCLUSION

This work is a first investigation of the use of CNN for image reconstruction in astronomy. We proposed a simple but efficient model and numerical experiments have shown very encouraging performances both in terms of reconstruction and computational speed. Future works will investigate more complex PSF such as the one of radio-interferometric telescopes [5], [3] and extensions to hyperspectral imaging where 3D image reconstruction will require efficient reconstruction [6], [22]. Finally the linear convolution model with noise is limited and we will investigate datasets obtained using more realistic simulators such as MeqTrees [23] for radio-interferometry or CAOS [24] for optical observations.

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