Inpainting RFI in Visibility Waterfall Plots

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PHYS 489 Project Proposal
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The Hydrogen Epoch of Reionization Array (HERA) is a radio interferometer located in South Africa. HERA is part of an international effort to map the universe during the Epoch of Reionization using 21-cm cosmology techniques [1, 2]. During this period and the Dark Ages that preceded it, neutral hydrogen emitted photons as its spin states underwent changes, known as 21-cm emission [3]. This radiation could allow us to better understand aspects of the early universe such as properties of the first galaxies and the evolution of large-scale structure [1].

Data from HERA is returned as visibility waterfall plots of local sidereal time (LST) vs. frequency. Visibility is a complex number that results from a Fourier transform on the brightness of the sky [4]. In practice, HERA data may be contaminated by sources such as radio frequency interference (RFI), a term applied to transmissions within the observed frequency band from non-celestial sources [5]. These irregularities must be accounted for in order to further analyze the data.

Machine learning models are able to identify the presence of RFI, as well as delineate it directly in waterfall plots [6]. The next step is to inpaint: to fill in missing data values masked by RFI. Two algorithms currently serve this purpose: a Gaussian technique, and CLEAN [7]. The former draws Gaussian-distributed numbers in a way that respects priors on the data's covariance. CLEAN deconvolves data with the assumption that the original image consists of point sources in Fourier space (i.e. sinusoids in the original frequency space). Disadvantages of both include a lack of tailoring for RFI, which exhibits certain patterns that we can exploit. Also, since CLEAN is a nonlinear algorithm, it's difficult to ascertain where and how prediction errors originate without copious simulation.

The current project proposes, to the best of our knowledge, the first machine learning approach to inpainting RFI. Neural networks have proven useful in a variety of astrophysical problems [8], including inpainting cosmic microwave background signals [9, 10]. Image inpainting is also an active subfield in computer vision, so we can additionally draw inspiration from recent developments there (e.g. [11, 12, 13]).

In our case, neural networks should also address the aforementioned difficulties with the Gaussian algorithm and CLEAN. Potential directions include regression with Convolutional Neural Networks (CNNs), deep neural networks well-suited to image data, and generative methods such as Generative Adversarial Networks and Variational Autoencoders. The latter two are more computationally complex, and so we will explore them after CNNs.

Logistically, I will meet with Adrian and Siamak weekly. We will aim to follow the PHYS 489 course structure, ideally having a model yielding positive results by mid-March. We will use the remainder of the semester to iterate, improve performance, experiment with alternate model architectures, and write the final report.

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