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Exploration of Machine Learning for Signal Processing Topics in Image Denoising

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Summary

In this paper, I provide a process-oriented description of my work on a self-study course I designed, the purpose of which was to continue learning about the material covered in 02417 *Machine Learning for Signal Processing*.

Introduction

My purpose in creating this self-study course was three-fold: to buiild an understanding of what the field of machine learning for signal processing looks like, to learn about cutting-edge research in the field and to see how the material could be applicable to topics I find personally interesting, to determine if it is a topic I could see myself pursuing professionally in the future.

To accomplish this, my original plan for the semester was to do a literature review, learn about and implement one or two topics from a research paper, and apply it to a topic I find interesting. In reality, I diverged from this plan due to unexpected challenges I faced. My actual progress throughout the semester can be find in the index below. I have divided my work into two sections: a literature review and practical part. These sections contain information about specific actions I took as well as the insights I have gained from it. Moreover, I finish this paper with a reflection of lessons I learned from the process overall.

Literature Review

As stated above, my intention behind this section was to develop an understanding about the field of machine learning for signal processing: what topics it entails, what topics are new and popular, how all the topics are related and how they are applied.

In order to accomplish this, I explored papers based on keywords on Google Scholar as well as what prominent and interesting figures in the field were working on. All the papers which I read that ultimately helped me reach the above stated goal can be found in a Zotero folder I used to keep track of my reading journey. [1] I will also not cite my insights from this section to specific papers (unless I mention those papers explicitly) because I have thoroughly labeled and divided the entries in my Zotero folder.

In this paper, I will go through the overall mental model I have formed about the field, some interesting specific technical ideas, and applications.

For me, the best way to make sense of many sources of information is to make a mind map. The reader can find my mind map of research in Machine Learning for Signal Processing in Figure 1.

From the figure, one can see that I gravitated towards the inverse problem and sparsity promoting algorithms in particular, as I was trying to narrow down my research.

Out of the topics I learned about, the ones I found particularly interesting and useful were graph signal processing, algorithm unrolling, diffusion and plug-and-play priors. Graph

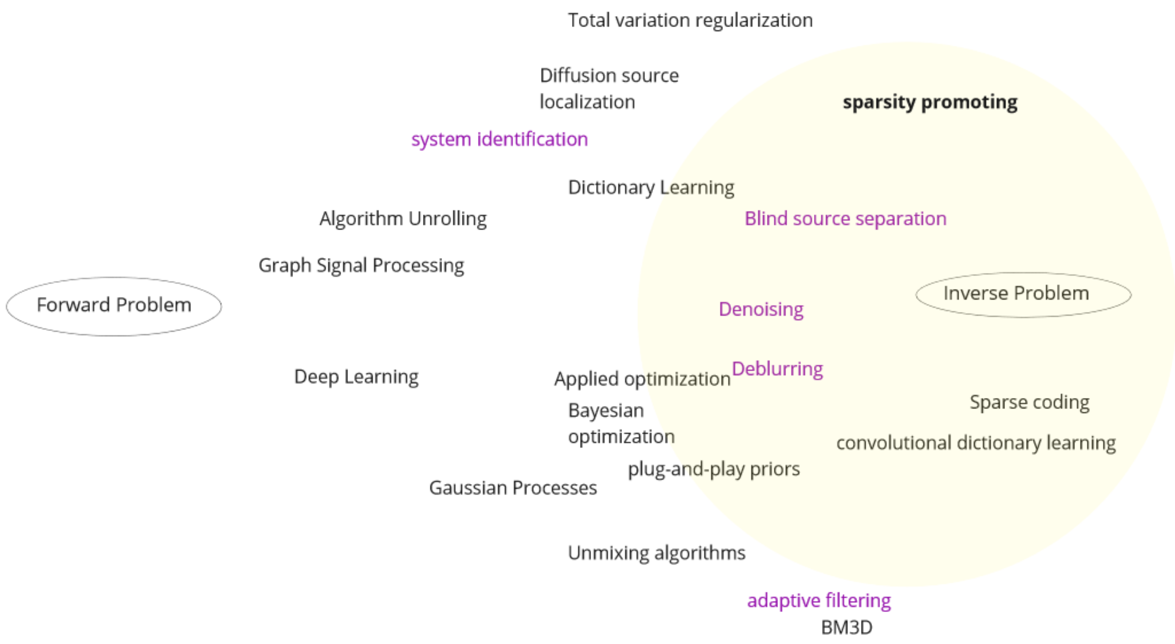

Figure 1: Mind map of concepts encountered in literature review

signal processing is an extensive subject area based on Rethinking of signal processing problems as graphs, and then solving them using graph theory. Diffusion is the concept of solving inverse problems by modeling the noise in sensor data as a noise source being diffused and then solving the system using partial differential equations. Plug-and-play priors is the idea of casting image restoration tasks as optimization problems, the plugg and play part comes from using ("plugging in") advanced techniques for the prior term. Finally, since later on, I create some algorithm unrolling algorithms, I will not describe it here.

Applications

Even when I first started studying signal processing in my bachelors, I found the subject interesting but could not relate to any of the applications I studied in class or during my internships in domain-adjacent subjects. Therefore, I found this subject particularly important for my personal journey in this domain.

I found that signal processing, and especially machine learning applicable signal processing, shows up in many unexpected fields. Signal processing will show up in any field where data can be obtained with sensors. However, the scope of what can be measured with sensors is larger than I imagined. Among others, signal processing is used to detect forgeries and generate insights in art conservation, measure micro-biological phenomenon like bio-luminescence, design controls in building development and the electricity grid, and as a part of smart agriculture. The topic which I found most promising in terms of how much it uses signal processing and how applicable it is is hyperspectral imaging.

Hyperspectral imaging is the practice of using image sensors that extra information from multiple wavelengths, beyond the visible ones, to learn about phenomena on spatial, temporal and domain-relevant levels. I would personally like to pursue a career in an environmentally-adjacent field, and found that there are entire organizations, such as the Finnish Geospatial Research Institute [2] which are dedicated to using signal processing technologies, mostly hyperspectral imaging, towards conservation. For example, researchers from this organization have used signal processing and hyperspectral imaging to do autonomous detection of bark beetle damage [3], or deep learning classification on measuring forest biodiversity. Technically, hyperspectral imaging is still a developing field that is using cutting-edge research to overcome shortcomings. For one, researchers are still improving the interpretability of hyperspectral images, especially those from low cost sensors, in order to make the technology more accessible. Another active research area is improving the information extraction from these images: these is image segmentation, which aims to classify different parts of images, and target detection, to autonomously identify desired clusters from images.

One reliable source of hyperspectral images for conservation tasks is Google Earth Engine. [4] This Google platform is a free, mutli-petabyte large cloud database of hyperspectral images that have been used by researchers in the past to create dozens of research papers on the topic of conservation. Being such a widely-used platform is one of its main benefits, because there exists thorough documentation on how to use it and is accessible in different formats. Although I was not able to extend my algorithm implementations to real-world applications due to time constraints, I was planning to analyze a dataset from this platform and would recommend it to others who are looking to do similar projects.

Algorithm Implementations

Originally, my plan for implementing an algorithm consisted of finding a paper that was technically interesting and applicable to hyperspectral imaging, learning everything necessary to implement that topic, and writing my own implementation in Python. As I explain in Section Process Reflection, I was not able to go through with that plan. Instead, I picked up bits and pieces of a variety of different topics in machine learning and signal processing, and created implementations of algorithms from two different papers: *Unrolled Optimization with Deep Priors* [5] and *Algorithm Unrolling* [6]. I also did a series of small experiments to build up my knowledge in these topics and explored using the code associated with *Deep Image Priors*. [7] In this section, I will describe the actions I took and what I learned from them, dividing the information into subsections based on the papers the explorations were inspired by. For each topic, I will describe what experiments I conducted and what I learned overall. The reader can find a more technical description of the algorithms used in the Jupyter notebooks where the experiments are conducted.

Unrolled Optimization with Deep Priors

This paper was the first from which I implemented an algorithm. I chose it because it seemed to be a straightforward application of algorithm unrolling.

However, when I started my implementation, I realized there were a lot of things that I did not understand. I realized that many terms which I thought I knew, I wasn't familiar with in the way they were being used in the paper. For example even though I was familiar with optimization, the authors wrote in a number of assumptions used in theoretical optimization. During my exploration process, I found one code implementation of this paper [8] and one research report from a student group who implemented it [9]. These sources helped me realize what I didn't know and finish my implementation. For example, it was through these sources that I not only learned what a residual neural network was, but that this paper was actually describing one.

Furthermore, it was through this paper that I learned about image restoration training sets and evaluation methods. I created a data processing script based on the author's description, and learned how to check that the data is set up correctly despite the large amount of images. I also learned that PSNR is one of the most widely used methods to evaluate image denoising algorithms.

In the end, my algorithm did not perform as well as the authors' and I believed that I had an issue with my code that I couldn't understand, so I decided to implement simpler algorithms that shared the same concepts.

Unrolled Algorithms and ISTA

After my "failed" attempt with unrolled optimization with deep priors, I decided to start with a simpler unrolled algorithm example. In the review paper on Unrolled Algorihtms [6], unrolled ISTA was mentioned. I considered implementing this even during my literature review, but decided not to because I wasn't sure if it could actually be used for denoising. However, at this point, it seemed like a good step, since it was an algorithm I was familiar with from 02477 and thus a stepping stone to master unrolled algorithms.

My excursion with this concept began with a series of lectures where I taught myself the optimization terms from the two papers that I did not understand. Among other things, I learned that stochastic gradient descent is not applicable to all functions and that the proximal gradient is one of the methods you could use instead, given certain assumptions.

I recreated the unrolled ISTA implementation hihglighted in the Unrolled Algorithm review paper. [6] One of the things I learned while doing this is how to build a dataset and neural network model from scratch. Up until now, I would always use an example model from class or a similar project as the base to my code. Because this network was based on a couple of equations however, I could not do that. During this process I ran into bugs with the dimensions of the inputs and batches and thus had to more critically consider what each line in the code was doing.

Deep Image Priors

Deep Image Priors is a topic that I invested multiple hours in learning, but that I do not have any code written for. Therefore, in this section I will explain how I went about learning the subject and summary of it.

Deep Image Priors is an algorithm that was developed by Dmitry Ulyanov in 2018. The author has created a series of resources online about the subject, include a github repo [10], a 1 hour video presentation [11] and a website [12]. I studied all three sources and another Medium article describing the subject as well [13].

Based on this research, i have developed the following mental model about it:

The main idea of the algorithm is that you can restore or recover an image by only using that one image (ie not having to train on many images). This is done by searching for the image transformation in the space of neural network parameters instead of image space. Functionally, this also looks like learning the noise on the image.

You can formulation image restoration as an optimization task that's composed of a composite function. Overall, the optimization task represents finding the best image x in an image space representing all images and comes from Bayesian MAP. One term in the function represents the loss, ie the data term; the other represents the image prior.

Instead of having your optimization function have x, the image, as the parameter, you can rewrite it as a function of θ. You can do this because the mapping from θ to x is surjective (ie every image can be mapped to a set of θ). Thus we get rid of the prior term and now find a set of thetas that minimize the loss between the predicted image and the corrupted image.

In practice, we start with an image that is pure noise, and pass it through an arbitrary function. We then calculate the loss between that and our original image. The result of that gets added to our new θ parameters, which update our function. Then, we keep iterating through the same process for a predetermined number of iterations.

Process Reflection

I think some of the most valuable lessons I learned from this project were from being reflective of how I approached my work. I was not able to work on the third task that I set out to do , applying the algorithms, and I believe that the reasons be summed up to one theme: the fear of failure.

I realized that my desire to produce a good result stopped me from being able to engage deeply with the material. One way this manifested was me spending a long time deciding on a topic after my literature review. For a couple of weeks, I went back and forth between reading about implementations, blind source separation and image restoration, unable to choose a paper to emulate. I was hesitant to choose any one area of signal processing to focus on, because I could not fully understand what was happening in the papers, so I couldn't be sure if I could create something "meaningful" with the results. To overcome this, I tried looking for and reading a lot of sources about the subjects, which ultimately were not helpful. Instead, I should have dedicated some time to understanding a topic to the point where I could decide for myself if it would be worthwhile or not, and why. I was scared that I would lose time learning something I didn't need, but since my goal with this project was to learn, the process itself would have been meaningful. Specifically, one thing I would do differently is to explore the feasibility of using some algorithm or process by starting with very small examples, and slowly adding complexity that would target exact ideas about feasibility. That way, I would gain a greater intuition for the underlying math concepts and applications.

Conclusion

Although I did not accomplish all the goals I set out to do, I believe that I fulfilled my overall mission. For one, during this project, I gained at least a partial overview of what the machine learning for signal processing field does and what they work on, and I found applications that were personally meaningful to me and that I could see myself exploring in the future. Also, I went through the process of finding material in this field and implementing new methods. By doing this, I gained experience on how to approach problems in this field and what practices would be good to have in the future.

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