**Course Title**

Algorithmic Aspects of Computational Imaging: Mathematical and Machine Learning-based Methods

**Course Code**

ECE 458

**Semester/Year**

Spring 2024

**Lectures**

Tue and Thu at 4:50-6:05 PM in Harkness Room 210

**Tutorials**

TBD

**Instructor**

Canberk Ekmekci

**Office**

Computer Studies Building 633

**Email**

cekmekci@ur.rochester.edu

**Office Hours**

Thu at 2:00-4:00 PM

**Course Website**

Blackboard will serve as a central hub for accessing course materials, assignments, announcements, and resources. Please ensure regular access to Blackboard to stay updated on course-related information and materials. For personal communication or queries, please contact the instructor via email. To expedite responses, include "[ECE458-S24]" in the subject line of your email. If you encounter any technical issues or require assistance accessing the website, please notify the instructor promptly.

**Course Description**

This course is structured into two parts. The first part will cover the fundamentals of computational imaging, including (1) physics-based modeling of the observation process for various computational imaging problems ranging from medical imaging problems to image restoration problems; (2) regularization-based image reconstruction methods, e.g., Tikhonov regularization, non-quadratic regularization, total variation regularization, wavelet domain regularization, and compressive sensing; and (3) optimization methods such as gradient-based optimization methods, proximal methods, and alternating direction method of multipliers. The second part of the course will focus on recent advancements in computational imaging and cover several state-of-the-art learning-based image reconstruction methods. In particular, dictionary learning, deep learning-based pre-processing and post-processing techniques, deep image priors, deep algorithmic unrolling, deep equilibrium models, Plug-and-Play Priors, Regularization by Denoising, Multi-Agent Consensus Equilibrium, deep generative model-based Bayesian inversion methods, and Bayesian neural network-based image reconstruction methods will be covered.

**Course Objectives**

There are two main objectives of this course:

1. To provide comprehensive treatment on state-of-the-art mathematical and machine learning-based solution techniques that have been used for inverse problems arising in imaging applications.
2. To equip participants with the ability to apply the methodologies taught in this course in their research endeavors.

Please note that this course does not center on a specific imaging application. Instead, we will illustrate concepts using examples drawn from diverse imaging applications.

**Prerequisites**

This course assumes a foundational understanding of signals and systems, calculus, linear algebra, probability theory, and basic programming in Python. If you have concerns about meeting these prerequisites or need further clarification, please reach out to the instructor for guidance.

**Grading Policy**

The evaluation process in this course revolves around two key components:

1. Homework: Each homework assignment will feature a combination of problems and programming exercises. A total of 8 assignments will be distributed throughout the term, constituting 50% of the final grade. The number of assignments might change based on the topics covered and the pace of the class; however, the total grade distribution will remain constant.
2. Final Project: The final project holds paramount importance, constituting 50% of the overall grade. This comprehensive task allows for in-depth exploration and application of course

concepts. Specific details outlining the final project guidelines, requirements, and the evaluation criteria will be provided during class sessions to ensure clarity.

Timely submission of assignments is encouraged to ensure smooth progress and timely feedback. While late submissions are generally discouraged, valid reasons such as health issues or personal emergencies may be considered for possible extensions.

**Books and Other Resources**

This course utilizes diverse resources including research articles, excerpts from books, and online materials. The list of suggested readings, talks and tutorials will be accessible through Blackboard.

**Academic Honesty**

Students are expected to uphold the principles outlined in the Academic Honesty Policy of the University of Rochester. Further details can be found at http://www.rochester.edu/college/honesty.

**Tentative Schedule**

| Date | Description |
|---|---|
| Thu 01/18 | Introduction, course logistics, motivating demonstrations |
| Tue 01/23 | Fundamentals of observation models, discretization |
| Thu 01/25 | Analytical and algebraic reconstruction methods |
| Tue 01/30 | Ill-posed inverse problems, variational modeling |
| Thu 02/01 | Tikhonov regularization, conjugate gradient method |
| Tue 02/06 | Sparsity promoting regularization |
| Thu 02/08 | Optimization primer |
| Tue 02/13 | FISTA and ADMM |
| Thu 02/15 | Compressed sensing |
| Tue 02/20 | Regularization parameter selection problem |
| Thu 02/22 | Recap |
| Tue 02/27 | Dictionary learning |
| Thu 02/29 | Pre and post-processing type deep learning-based image reconstruction methods |
| Tue 03/05 | Pre and post-processing type deep learning-based image reconstruction methods |
| Thu 03/07 | Plug-and-Play (PnP) priors framework |
| Tue 03/12 | Plug-and-Play (PnP) priors framework |
| Thu 03/14 | Spring Break |
| Tue 03/19 | Spring Break |

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| Thu 03/21 | Regularization by Denoising (RED) framework |
| Tue 03/26 | Deep algorithmic unrolling framework |
| Thu 03/28 | Multi-agent consensus equilibrium (MACE) |
| Tue 04/02 | Posterior sampling with generative models |
| Thu 04/04 | Posterior sampling with generative models |
| Tue 04/09 | Posterior sampling with generative models |
| Thu 04/11 | Bayesian neural network-based image reconstruction methods |
| Tue 04/16 | Bayesian neural network-based image reconstruction methods |
| Thu 04/18 | Robustness of deep learning-based image reconstruction methods |
| Tue 04/23 | Buffer lecture 1 |
| Thu 04/25 | Buffer lecture 2 |
| Tue 04/30 | Final project presentations |