General Course Information

Motivation and overview

Imaging is essential to scientific progress. With the innate human ability for visual information processing, seeing is believing, seeing is understanding, and seeing is even central to hypothesizing. Unconventional sensing, sophisticated modeling, and abundant computational resources are revolutionizing imaging. Beyond images for human consumption, whatever is worth measuring is often measured as a function of space and thus is also imaging. A prime example is the imaging in an autonomous vehicle that is used by that vehicle's navigation system rather than viewed by a person. Many of today's emerging imaging modalities have no analogue to the use of optics to produce a focused image; instead, spatial resolution in two or more dimensions comes from solving an inverse problem. Make no mistake: techniques such as synthetic aperture radar, computed tomography, MRI, and others have existed for decades; however, the essential role of sophisticated signal modeling, information representation, and computation is only recent.

The purpose of this course is to create a *learning community* that is focused on the topic of *computational imaging*. Since computational imaging is at the intersection of signal processing, computation, vision, statistics, and optics, along with other areas of physics for certain modalities and electronics for the understanding of device behavior, many backgrounds are welcome and potentially valuable to this community. The instructor's contributions will focus on the signal processing aspects of computational imaging, including the formulation and solution of inverse problems. However, all students should be aware that the instructor is merely a guide. Students will be expected to make contributions to the learning of the entire group, for example through presentation of papers.

Catalog description

Principles and methods of reconstructing images and estimating multidimensional fields from indirect and noisy data; general deterministic (variational) and stochastic (Bayesian) techniques of regularizing ill-posed inverse problems; relationship of problem structure (data and models) to computational efficiency; impact of typically large image processing problems on viability of solution methods; problems in imaging and computational vision including tomography and surface reconstruction. Computer assignments.

Lectures

Tuesdays and Thursdays 1:30 pm – 3:15 am Room PHO 202

An online document with a rough schedule of lecture topics will be updated throughout the semester. Office hours are by appointment because there are few times when all registered students are free.

Prerequisites

The formal undergraduate prerequisites are ENG EC 516 (Digital Signal Processing) and ENG EC 505 (Stochastic Processes). Informally, background in linear algebra is essential; those without good working knowledge of linear algebra should expect to review intensively in the first few weeks of the semester.

High-level organization

Computational imaging has many aspects to understand and to which one can make novel contributions. One simple dichotomy is between the *formulation of inverse problems* and the *computational solution of these inverse problems*.

The formulation of inverse problems includes the design of equipment, configurations, and data collection protocols to yield data; the modeling of that data; and the analysis of what could be achieved in principle with that data. Conversions of continuous-domain, continuous-valued quantities to digital files is central in this work, generalizing familiar sampling theory to multidimensional function spaces.

The computational solution of inverse problems includes the formulation of optimization problems to include regularization; machine learning to create implicit regularizers; and algorithms to compute solutions. Explicit and implicit probabilistic modeling is prominent in finding the most meaningful and useful solutions.

While it may be natural to think that one must first formulate a problem before solving it, the course will first emphasize computational solutions and later discuss formulations. Having some familiarity with computational tools for inverse problems will make it easier to experiment with variations on formulations.

Texts

The primary text on solving inverse problems is:

- Charles A. Bouman, *Foundations of Computational Imaging: A Model-Based Approach* (SIAM, 2022)

Part of the course will be in a "flipped" format using videos of Charlie Bouman online.

The primary texts on formulating inverse problems are (note online access through the BU library):

- Per Christian Hansen, Jakob Sauer Jørgensen, William R. B. Lionheart, eds., *Computed Tomography: Algorithms, Insight, and Just Enough Theory* (SIAM, 2021)
- Per Christian Hansen, *Discrete Inverse Problems: Insight and Algorithms* (SIAM, 2010)

Some other potentially useful books include:

- Mario Bertero, Patrizia Boccacci, and Valeria Ruggiero, *Inverse Imaging with Poisson Data: From cells to galaxies* (IOP Publishing, 2018)
- Richard E. Blahut, *Theory of Remote Image Formation* (Cambridge Univ. Press, 2004)
- Martin Hanke, *A Taste of Inverse Problems: Basic Theory and Examples* (SIAM, 2017)
- Frank Natterer and Frank Wübbeling, *Mathematical Methods in Image Reconstruction* (SIAM, 2001)
- Martin Vetterli, Jelena Kovačević, and Vivek K Goyal, *Foundations of Signal Processing* (Cambridge Univ. Press, 2014)
- Curtis R. Vogel, *Computational Methods for Inverse Problems* (SIAM, 2002)

Web resources and web-enabled interaction

The Blackboard system at `https://learn.bu.edu` will be the primary means for distributing course materials.

Homework

Tentatively, there will be 7 homework assignments, assigned approximately every other week. Working through the problems carefully is a crucial part of the learning process. Collaboration in the form of joint problem solving with classmates is permitted and even encouraged. All written submissions should reflect your understanding; do not copy a solution from any other source.

Term project

The term project is your opportunity to supplement the fundamental material covered in the homework assignments with in-depth study of one topic. The instructor will attempt to guide you so that the project is an effective learning experience and yields significant results. You may choose any topic related to the tools and techniques of the course. Your project may overlap with your current thesis research; in fact, this is encouraged. However, it is a violation of academic conduct standards if you:

- use work completed before the current semester;
- use the same project for more than one course;
- include joint work without clearly indicating your contribution (e.g., you should inform the instructor if your research advisor has provided significant guidance on your project); or
- use the work of others (including co-authored work) without attribution.

If you are in doubt about scholarly standards for citing prior work, ask the instructor. If plagiarism is noticed, it will not be tolerated. More subtle than the issues above: *hold yourself to a standard of completing work for the term project that you would not have done otherwise.* You may work individually or in groups of two. A group of two should produce a single final report; whether groups of two are given longer presentation time slots will be determined later. Groups of two will be held to a higher standard, and group members are not guaranteed equal grades.

Deliverables. The project has several deliverables to ensure that you keep the instructor up to date on progress.

- Oct 6: Project concept ($\frac{1}{3}$ page) – very short description
- Oct 20: Project proposal (1 page) – description including details on project scope
- Nov 17: Project update (3 pages) – update
- Dec 8: Project report – in the style of a conference paper, with length appropriate for the necessary detail

Course grade

The scores on graded elements will be combined with the following weighting to give a preliminary grade:

Class participation:	20%
Homework:	40%
Term project:	40%