UNIVERSITY OF CALIFORNIA, DAVIS
Department of Electrical and Computer Engineering

EEC263 Optimal and Adaptive Filtering Spring 2010

Course Information

Course Content: Geometric interpretation and orthogonality property of linear least-squares estimates. FIR Wiener filter, Levinson recursions, lattice filters. Noncausal and causal Wiener filtering. Wiener-Hopf equation, spectral factorization. State-space models driven by white noise. Innovations process and Kalman filtering recursions. Steady-state behavior of Kalman filters. Algorithms for Kalman filtering, smoothing. Iterative solution of linear least-squares estimation problems. Introduction to adaptive filtering filtering: stochastic gradient/LMS and recursive least-squares (RLS) algorithms. Convergence and steady-state performance of adaptive filters: bias, excess mean-square error, and speed of convergence. The Infomax principle and adaptive ML estimation.

Prerequisite: EEC260, Random Signals and Noise.

Web page: http://www.ece.ucdavis.edu/~levy/eec263.html

Schedule: Lectures: M-W 2:10-4:00pm, 263 Olson

Instructor: Bernard C. Levy

Office: Room 3183, Kemper.

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Office Hours: Tu 3:30-5:00pm, Room 3183, Kemper

Textbook: *Statistical Digital Signal Processing and Modeling*, by M. Hayes, J. Wiley, 1996.

In addition to the required text, whose coverage of Kalman and adaptive filtering is rather sketchy, several other sources, such as class notes and journal articles, will be used for the course. The following books may also be worth consulting.

(i) Wiener and Kalman filtering:

T. Kailath, A. H. Sayed, and B. Hassibi, *Linear Estimation*, Prentice-Hall, Upper Saddle River, NJ, 2000. Provides an encyclopedic coverage of Wiener and Kalman filtering.

A. S. Willsky, MIT lecture notes for course 6.433 "Recursive estimation," 1987. An exceptionally clear presentation of Kalman filtering methods.

J. L. Speyer and W. H. Chung, *Stochastic Processes, Estimation, and Control*, Soc. for Industrial and Applied Math., Philadelphia, PA, 2008. A rigorous presentation of discrete- and continuous-time Kalman filtering, and of risk-sensitive filtering.

D. Simon, *Optimal State Estimation– Kalman, H-infinity, and Nonlinear Approaches*, Wiley-Interscience, Hoboken, NJ, 2006. A rather mechanical book, but covers H^∞ and nonlinear filters, including unscented and particle filters.

(ii) Statistical signal processing:

D. G. Manolakis, V. K. Ingle, and S. M. Kogon, *Statistical and Adaptive Signal Processing*, McGraw Hill, Boston, 2000. Very comprehensive coverage of statistical signal processing techniques.

C. Therrien, *Discrete Random Signals and Statistical Signal Processing*, Prentice-Hall, 1992. An elementary coverage of the Levinson recursions, lattice filters, Wiener and Kalman filtering.

(iii) Adaptive signal processing:

A. H. Sayed, *Adaptive Filters*, Wiley/IEEE Press, 2008. This comprehensive book covers in detail stochastic gradient and least-squares adaptive filtering methods and includes several computer projects. Employs the energy conservation approach (not as general as the ODE/averaging method) for analyzing the convergence and performance of adaptive algorithms.

S. Haykin, *Adaptive Filter Theory*, 4th edition, Prentice-Hall, 2001. Another lenghty but not always accurate coverage of adaptive filtering.

A. Benveniste, M. Métivier, and P. Priouret, *Adaptive Algorithms and Stochastic Approximations*, Springer Verlag, Berlin, 1990. A thorough derivation of the ODE/stochastic averaging method for analyzing the convergence and performance of adaptive algorithms. The guide of Section 2.4, together with Theorems 1, 2 and 3 of Chapter 3 can be used to analyze any adaptive algorithm without needing to understand subsequent book chapters.

Enrollment: Enrollment in this course is handled through SISWeb at http://sisweb.ucdavis.edu. The last day to add the the course is Tuesday, April 13, 2010, and the last day to drop the course is Friday April 23, 2010.

Problem Sets: Problem sets will be assigned approximately every other week on Wednesday, and will be due the following Wednesday in class. Problem sets will be graded coarsely on a scale of 0 to 5.

Computer Projects: A few MATLAB projects will be assigned, approximately every other week, in alternance with problem sets. If you do not have already access to MATLAB you should get an ECE Dept. computer account at the beginning of the quarter.

Term paper or project: In addition to the problem sets and MATLAB assignments, you will be asked to select a topic for a term paper or project. A list of possible topics will be distributed in class. The term paper or project report should be approximately of 15 to 20 pages in length. It will be due on Wednesday, June 9 at 5pm. Ideally, reports should be submitted to the instructor by email in pdf format.

Grading: The course grade will be based on a weighted average of the problem sets, MATLAB exercises, and term paper scores. The problems sets and MATLAB assignments will each be worth 25% of the total score, and the term paper/project will count as half of the total course grade.

Posting of Grades and Return of Work: Course grades and statistics will be posted on the MyUCDavis web site.

Course Outline

A tentative lecture schedule is given below.

Lecture Number	Date	Topic
1	3/29	geometric interpretation and orthogonality property
		of linear least-squares estimates
2	3/31	FIR Wiener filter, linear prediction
		Levinson recursions
3	4/05	lattice filters
4	4/07	noncausal IIR Wiener filter
		causal IIR filtering
		Wiener-Hopf equation
5	4/12	spectral factorization
		causal Wiener filter
6	4/14	IIR Wiener prediction and smoothing
7	4/19	Gauss-Markov state-space models
		and their statistics
8	4/21	innovations process
		Kalman filter recursions
9	4/26	steady-state behavior of Kalman filters
10	4/28	square-root algorithms
11	5/03	smoothing
		two-filter and double sweep smoothers
12	5/05	iterative solution of least-squares estimation problems
		gradient and Newton iterations
13	5/10	steepest descent method for FIR filtering
		LMS algorithm
14	5/12	method of least-squares
		recursive lest-squares (RLS) algorithm
15	5/17	state-space formulation of RLS
		square-root RLS algorithms
16	5/19	ODE method for the analysis of adaptive algorithms
		convergence and performance of LMS algorithm
17	5/24	convergence and performance of RLS algorithm
18	6/26	adaptive ML estimation, Infomax principle
	5/31	Memorial Day Holiday
19	6/02	example: blind equalization

Drop Date: Friday, April 23.
Term paper/project report due date: Wednesday, June 9, 5pm.