ENEE 739E
Advanced Topics in Signal Processing: Sparse Statistical Signal Processing and Learning
Spring Semester, 2015

Handout # 1: General Information

Lecture: Monday and Wednesday: 3:30 pm to 4:45 pm in CHE 2136

Website: https://myelms.umd.edu/login

Instructor: Dr. Piya Pal
Office: AVW 2305, Ext.: 8028
Office Hours: Mon. 5:00-6:00 pm (also by appointment)
Email: ppal@ece.umd.edu

TA: Mr. Heng Qiao
Office: AVW 4444
Office Hours: Friday. 5:00-6:00 pm
Email: qiaoheng@umd.edu

Grading: Project: 85 %
Written Paper Reviews: 15 % (about 2 or 3)

Course Objectives and Syllabus: ENEE 739E is a graduate level special topics course in modern signal processing, which introduces the fundamentals of sparse statistical signal processing. Theoretical topics will include signal representation in terms of frames and bases, Compressive Sampling, Matching Pursuit and Basis Pursuit algorithms, analysis of linear programming techniques for sparse reconstruction, LASSO, Restricted Isometry Property, Random matrices, low rank matrix recovery, Lifting techniques, Robust Principal Component Analysis (PCA), and special topics in statistical learning such as Bayesian Compressed sensing, Sparse Subspace Clustering, Blind Deconvolution, Non Negative Matrix Factorization, and so forth. You will be able to find application of these theoretical tools in a number of areas such as image and video processing, computer vision and machine learning, data analysis. The core topics of this course consist of:

1. **Signal Representation and Sparsity:**
   Reading: [1, 5, 6, 7, 8, 9, 10, 11]
   Lectures (tentative): Feb. 2-Feb. 11

   - Frames and Bases.
   - Coherence, Welch Bound and Grassmannian Frames.
   - Greedy Pursuit Algorithms.

- Denoising.

2. **Compressed Sensing and Sparse Reconstruction**
   Reading: [4, 12, 13, 14, 19, 15, 16, 17, 18, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29]
   Lectures (tentative): Feb 16 - March 11

   - Geometry of l_1 minimization and relation to sparse solutions.
   - Null Space Property.
   - Restricted Isometry Property (RIP) and the JL Lemma.
   - Analysis of Basis Pursuit
   - Compressive Sampling : Random and Deterministic matrices. Scaling laws for sample size.
   - Robust and Stable Recovery via LASSO
   - Thresholding algorithms.

3. **Low Rank Matrix recovery**
   Reading: [30, 31, 32, 34, 35, 36, 37]
   Lectures (tentative): March 23-April 6

   - Nuclear Norm Minimization.
   - Robust Principal Component Analysis (PCA).
   - Lifting techniques and rank-1 solutions.

4. **Special Topics**
   Reading: Will be provided
   Lectures (tentative): April 8-20
   Topics may include some of the following

   - Bayesian Compressed Sensing.
   - Sparse Subspace Clustering.
   - Dictionary Learning.
   - Non Negative Matrix Factorizations.
   - Blind Deconvolution.

Evaluation Policy: The evaluation policy of this advanced graduate course will be based on a project and occasional paper reviews. The students are encouraged to propose a topic for the project which is aligned with their own research area and apply the theoretical concepts and algorithms learnt from this course to address the question of interest. For the project, you can either develop theoretical results, or work on real data. Project proposals are due by March 4. Each student will be required to deliver a 15 minute oral presentation of his/her work towards the end of the semester (tentatively between April 22 and May 12). Furthermore, to receive credit for the course, students must submit a final report, due in the week of May 11 (exact date to be announced).

Additionally, the students will be occasionally asked to read relevant research papers and write a short report reviewing the paper.

Academic Integrity: As a student of this course, you are responsible for abiding by the Code of Academic Integrity, administered by the Student Honor Council. You should be fully aware of the consequences of cheating, fabrication, and plagiarism. Please visit **http://www.shc.umd.edu** for more information on the Code of Academic Integrity.

References

[1] Stephane Mallat, *A wavelet tour of signal processing: the sparse way.* Academic press, 2008.

[2] Simon Foucart, and Holger Rauhut *A mathematical introduction to compressive sensing*. Boston: Birkhuser, 2013.

[3] Michael Elad, *Sparse and redundant representations: from theory to applications in signal and image processing.* Springer Science Business Media, 2010.

[4] Boyd, Stephen, and Lieven Vandenberghe, *Convex optimization.* Cambridge university press, 2004.

[5] D. L. Donoho and X. Huo, "Uncertainty principles and ideal atomic decomposition", *IEEE Trans. On Information Theory*, 47(7), pp. 2845-2862, 1999.

[6] M. Elad and A. M. Bruckstein, "A generalized uncertainty principle and sparse representation in pairs of bases", *IEEE Trans. On Information Theory*, 48, pp. 2558-2567, 2002.

[7] R. Gribonval and M. Nielsen, "Sparse decompositions in unions of bases", *IEEE Trans. on Information Theory*, 49(12), pp. 3320-3325, 2003.

[8] T. Strohmer and R. W. Heath, "Grassmannian frames with applications to coding and communication", *Applied and Computational Harmonic Analysis*, 14, pp. 257-275, 2004.

[9] A. Bruckstein, D.L. Donoho, M. Elad, "From sparse solutions of systems of equations to sparse modeling of signals and images", *SIAM Rev.* 51(1), pp. 34-81, 2009.

[10] J. A. Tropp, "Greed is good: Algorithmic results for sparse approximation," *IEEE Trans. On Information Theory,* 50(10), pp. 2231-2242, October 2004.

[11] D. Needell and J. A. Tropp, "CoSaMP: Iterative signal recovery from incomplete and inaccurate samples", *Applied Computational Harmonic Analysis*, 26, pp. 301-321, May 2009.

[12] E. J. Candes, M. Wakin, "An introduction to compressive sampling", *, IEEE Signal Process. Mag.* 25(2), pp. 2130, 2008.

[13] E. J. Candes, "The restricted isometry property and its implications for compressed sensing", *C. R. Math. Acad. Sci.* Paris 346, pp. 589-592, 2008.

[14] E. J. Candes, J. Romberg, T. Tao, "Robust uncertainty principles: exact signal reconstruction from highly incomplete frequency information", *IEEE Trans. Inform. Theor.*, 52(2), pp. 489-509, 2006.

[15] D. L. Donoho, "Compressed sensing", *IEEE Trans. Inform. Theor.*, 52(4), pp. 1289-1306, 2006.

[16] D. L. Donoho, "High-dimensional centrally symmetric polytopes with neighborliness proportional to dimension", *Discrete Comput. Geom.*, 35(4), pp. 617-652, 2006.

[17] D. L. Donoho, M. Elad, V. N. Temlyakov, "Stable recovery of sparse overcomplete representations in the presence of noise", *IEEE Trans. Inform. Theor.* 52(1), 618 (2006)

[18] D. L. Donoho, J. Tanner, "Sparse nonnegative solutions of underdetermined linear equations by linear programming", *Proc. Natl. Acad. Sci.* 102(27), pp. 9446-9451.

[19] E. J. Cand'es, J. Romberg, T. Tao, "Stable signal recovery from incomplete and inaccurate measurements", *Comm. Pure Appl. Math.* 59(8), pp. 1207-1223.

[20] R. G. Baraniuk, "Compressive sensing". *IEEE Signal Process. Mag.*, 24(4), pp. 118121, 2007.

[21] R. G. Baraniuk, M. Davenport, R. A. DeVore, M. Wakin, "A simple proof of the restricted isometry property for random matrices". *Constr. Approx.* 28(3), pp. 253-263, 2008.

[22] S. Dasgupta, A. Gupta, "An elementary proof of a theorem of Johnson and Lindenstrauss", *Random Struct. Algorithm.*, 22(1), pp. 6065, 2003.

[23] T. Cai, A. Zhang, "Sharp RIP bound for sparse signal and low-rank matrix recovery," *Appl. Comput. Harmon. Anal.* 35(1), pp. 7493, 2013.

[24] S. S. Chen, D. L. Donoho, M. A. Saunders, "Atomic decomposition by Basis Pursuit", *SIAM J. Sci. Comput.* 20(1), pp. 33-61, 1999.

[25] T. Blumensath, M. Davies, "Iterative thresholding for sparse approximations", *J. Fourier Anal. Appl.*, 14, pp. 629-654, 2008.

[26] I. F. Gorodnitsky and B. D. Rao, "Sparse signal reconstruction from limited data using FOCUSS: A re-weighted norm minimization algorithm," *IEEE Trans. on Signal Processing,* 45(3), pp. 600-616, 1997.

[27] B. Efron, T. Hastie, I. M. Johnstone, and R. Tibshirani, "Least angle regression", The Annals of Statistics, 32(2), pp. 407-499, 2004.

[28] J. A. Tropp, "Just relax: Convex programming methods for subset selection and sparse approximation", *IEEE Trans. on Information Theory,* 52(3), pp. 1030-1051, March 2006.

[29] G. M. James, P. Radchenko, and J. Lv, "DASSO: connections between the Dantzig selector and lasso", *Journal of the Royal Statist. Soc.* B, 71(1), pp. 127-142, 2009.

[30] M. Fazel, "Matrix Rank Minimization with Applications", PhD thesis, 2002.

[31] B. Recht, M. Fazel, P. Parrilo, "Guaranteed minimum-rank solutions of linear matrix equations via nuclear norm minimization", *SIAM Rev.* 52(3), pp. 471-501, 2010.

[32] E. J. Cands and Y. Plan. "Tight oracle bounds for low-rank matrix recovery from a minimal number of random measurements", *IEEE Transactions on Information Theory*, 57(4), pp. 2342-2359, 2009.

[33] E. J. Candes, X. Li, Y. Ma, and J. Wright. "Robust Principal Component Analysis?" *Journal of ACM,* 58(1), pp. 1-37.

[34] E. J. Candes and Y. Plan, "Matrix completion with noise" *Proceedings of the IEEE*, 98(6), pp. 925-936, 2009.

[35] E. J. Candes and T. Tao. "The power of convex relaxation: Near-optimal matrix completion", *IEEE Trans. Inform. Theory*, 56(5), pp. 2053-2080, 2009.

[36] R. Balan, P. Casazza, and D. Edidin. "On signal reconstruction without noisy phase", *Appl. Comp. Harm. Anal.,* 20, pp. 345-356, 2006.

[37] E. J. Candes, T. Strohmer and V. Voroninski, "PhaseLift: exact and stable signal recovery from magnitude measurements via convex programming" *Communications on Pure and Applied Mathematics*, 66, pp. 1241-1274, 2011.