EE641-Digital Image Processing II
Fall 2002
Reading List

1 Overview references

A good reference covering 1-D stochastic processes and Markov chains is [29]. An early paper by Dubes and Jain [13] also contains a nice overview of both continous and discrete random field models, and the book by Chellappa and Jain contains tutorial chapters on specified topics [10].

2 Gaussian Random Fields

The papers by Kashyap and Chellappa [11, 20] give a very good overview of 2-D Gaussian random field models and the related issues.

3 Mixture Distributions and the EM Algorithm

The reference [25] contains a high level tutorial overview. However, I recommend a careful reading of Baum's original 1970 paper [2] or his earlier paper [3] as the best method for learning the basic algorithm. Next I suggest reading a very nice paper by Aitkin and Rubin [1] to see how the EM algorithm can be applied to a standard problem such as clustering using Gaussian mixture distributions.

The paper by Wu [33] gives a clear overview of the basic convergence properties of the EM algorithm, however, for detailed proofs of convergence of the sequence of estimates, one can refer to [28].

The paper by Rabiner and Juang [27] is an excellent introduction to hidden Markov Models, but it does not contain much on the application of the EM (or equivalently Baul-Welch) algorithms to HMMs.

4 Discrete Markov Random Fields

The paper-back book by Kindermann and Snell [21] is an excellent introduction to MRFs.

The seminal paper by Besag [4] introduces and proves the Hammersley-Clifford theorem, and the paper by Onsager [26] derives an exact expression for the partition function of an Ising model in the limit as its size approaches infinity.

The later Besag paper [5] contains an clear and intuitive discussion of the application of MRFs to segmentation, and also introduces the ICM algorithm. The exact solution to binary MAP segmentation problems is contain in [18]. Geman and Geman introduces the Gibbs sampler, its application to MAP estimation, and prior model known as a line process in their well known paper [15]. Marroquin, Mitter, and Poggio introduce the MPM algorithm in [24], and Comer and Delp introduce the EM/MPM algorithm in [12]. Finally, Bouman and Liu present an early treatment of multiresolution MAP estimation in [7].

5 Continuous Markov Random Fields

Blake introduced the concept of the weak-spring model for MRF potential function design in [6]. Then D. Geman discussed potential function selection and introduced what-is-now-called "half-quadratic reqularization" in [14]. See [8] and [30] for an introduction to generalized Gaussian MRF models.

The original application of the EM algorithm to ML estimation of images from photon limited data was introduced by Shepp and Vardi in their well-known paper [32]. However, this work did not incorporate a prior distribution or penalty weighting in the optimization cost functional. Perhaps the earliest research on MAP estimation for tomography problems was contained in the somewhat obscure conference publications by S. Geman and McClure [16, 17]. Levitan and Herman also presented a framework for MAP image reconstruction using the EM algorithm in [23], but they did not present an algorithm for computing the solution for the tomography problem. Later, Hebert and Leahy presented the generalized EM algorithm (GEM) [19] which is an algorithm for computing the MAP reconstruction using EM. In [22], Lange studies the convergence properties the MAP reconstruction algorithms and the various prior models of the time.

Sauer and Bouman introduced a coordinate descent method for computing MAP estimates that does not depend on the use of an EM formulation in [31, 9]. This paper also introduces the computational methods of the ICD algorithm and the frequency analysis for convergence.

References

[1] M. Aitkin and D. B. Rubin. Estimation and hypothesis testing in finite mixture models. *Journal of the Royal Statistical Society B*, 47(1):67–75, 1985.

[2] L. Baum, T. Petrie, G. Soules, and N. Weiss. A maximization technique occurring in the statistical analysis of probabilistic functions of Markov chains. *Ann. Math. Statistics*, 41(1):164–171, 1970.

[3] L. E. Baum and T. Petrie. Statistical inference for probabilistic functions of finite state Markov chains. *Ann. Math. Statistics*, 37:1554–1563, 1966.

[4] J. Besag. Spatial interaction and the statistical analysis of lattice systems. *Journal of the Royal Statistical Society B*, 36(2):192–236, 1974.

[5] J. Besag. On the statistical analysis of dirty pictures. *Journal of the Royal Statistical Society B*, 48(3):259–302, 1986.

[6] A. Blake. Comparison of the efficiency of deterministic and stochastic algorithms for visual reconstruction. *IEEE Trans. on Pattern Analysis and Machine Intelligence*, 11(1):2–30, January 1989.

[7] C. A. Bouman and B. Liu. Multiple resolution segmentation of textured images. *IEEE Trans. on Pattern Analysis and Machine Intelligence*, 13(2):99–113, February 1991.

[8] C. A. Bouman and K. Sauer. A generalized Gaussian image model for edge-preserving MAP estimation. *IEEE Trans. on Image Processing*, 2(3):296–310, July 1993.

[9] C. A. Bouman and K. Sauer. A unified approach to statistical tomography using coordinate descent optimization. *IEEE Trans. on Image Processing*, 5(3):480–492, March 1996.

[10] R. Chellappa and A. Jain, editors. *Markov Random Fields: Theory and Applications*. Academic Press, Inc., Boston, 1993.

[11] R. Chellappa and R. L. Kashyap. Digital image restoration using spatial interaction models. *IEEE Trans. on Acoustics Speech and Signal Processing*, ASSP-30(3):614–625, June 1982.

[12] M. L. Comer and E. J. Delp. Segmentation of textured images using a multiresolution Gaussian autoregressive model. *IEEE Trans. on Image Processing*, 8(3):408–420, March 1999.

[13] R. Dubes and A. Jain. Random field models in image analysis. *Journal of Applied Statistics*, 16(2):131–164, 1989.

[14] D. Geman and G. Reynolds. Constrained restoration and the recovery of discontinuities. *IEEE Trans. on Pattern Analysis and Machine Intelligence*, 14(3):367–383, March 1992.

[15] S. Geman and D. Geman. Stochastic relaxation, Gibbs distributions and the Bayesian restoration of images. *IEEE Trans. on Pattern Analysis and Machine Intelligence*, PAMI-6:721–741, November 1984.

[16] S. Geman and D. McClure. Bayesian images analysis: An application to single photon emission tomography. In *Proc. Statist. Comput. sect. Amer. Stat. Assoc.*, pages 12–18, Washington, DC, 1985.

[17] S. Geman and D. McClure. Statistical methods for tomographic image reconstruction. *Bull. Int. Stat. Inst.*, LII-4:5–21, 1987.

[18] D. Greig, B. Porteous, and A. Seheult. Exact maximum a posteriori estimation for binary images. *J. R. Statist. Soc. B*, 51(2):271–278, 1989.

[19] T. Hebert and R. Leahy. A generalized EM algorithm for 3-D Bayesian reconstruction from Poisson data using Gibbs priors. *IEEE Trans. on Medical Imaging*, 8(2):194–202, June 1989.

[20] R. Kashyap and R. Chellappa. Estimation and choice of neighbors in spatial-interaction models of images. *IEEE Trans. on Information Theory*, IT-29(1):60–72, January 1983.

[21] R. Kindermann and J. Snell. *Markov Random Fields and their Applications*. American Mathematical Society, Providence, 1980.

[22] K. Lange. Convergence of EM image reconstruction algorithms with Gibbs smoothing. *IEEE Trans. on Medical Imaging*, 9(4):439–446, December 1990.

[23] E. Levitan and G. Herman. A maximum a *posteriori* probability expectation maximization algorithm for image reconstruction in emission tomography. *IEEE Trans. on Medical Imaging*, MI-6:185–192, September 1987.

[24] J. Marroquin, S. Mitter, and T. Poggio. Probabilistic solution of ill-posed problems in computational vision. *Journal of the American Statistical Association*, 82:76–89, March 1987.

[25] A. Mohammad-Djafari. Joint estimation of parameters and hyperparameters in a Bayesian approach of solving inverse problems. In *Proc. of IEEE Int'l Conf. on Image Proc.*, volume II, pages 473–476, Lausanne, Switzerland, September 16-19 1996.

[26] L. Onsager. Crystal statistics i. a two-dimensional model. *Physical Review Letters*, 65:117–149, 1944.

[27] L. R. Rabiner. A tutorial on hidden Markov models and selected applications in speech recognition. *Proc. of the IEEE*, 77(2):257–286, February 1989.

[28] E. Redner and H. Walker. Mixture densities, maximum likelihood and the EM algorithm. *SIAM Review*, 26(2), April 1984.

[29] S. M. Ross. *Stochastic Processes*. John Wiley & Sons, New York, 1983.

[30] S. S. Saquib, C. A. Bouman, and K. Sauer. ML parameter estimation for Markov random fields with applications to Bayesian tomography. *IEEE Trans. on Image Processing*, 7(7):1029–1044, July 1998.

[31] K. Sauer and C. A. Bouman. A local update strategy for iterative reconstruction from projections. *IEEE Trans. on Signal Processing*, 41(2):534–548, February 1993.

[32] L. Shepp and Y. Vardi. Maximum likelihood reconstruction for emission tomography. *IEEE Trans. on Medical Imaging*, MI-1(2):113–122, October 1982.

[33] C. Wu. On the convergence properties of the EM algorithm. *Annals of Statistics*, 11(1):95–103, 1983.