

Preface to the Third Edition

Most important advances in MRF modeling made in the past decade or so are included in this edition. Mathematical MRF models are presented in a newly added chapter. The following are the added contents.

- Mathematical MRF Models:
 - conditional random field, discriminative random fields,
 - strong MRF, \mathcal{K} -MRF and Nakagami-MRF,
 - MRF's and Bayesian networks (graphical models)
- Low-Level Models:
 - stereo vision, spatio-temporal models
- High-Level Models:
 - face detection and recognition
- Discontinuities in MRF's:
 - total variation (TV) models
- MRF Model with Robust Statistics:
 - half-quadratic minimization
- Minimization – Local Methods:
 - belief propagation, convex relaxation
- Minimization – Global Methods:
 - graph cuts

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Preface to the Second Edition

Progress has been made since the first edition of this book was published five years ago. The second edition has included the most important progress in MRF modeling in image analysis in recent years, such as Markov modeling of images with “macro” patterns (e.g., the FRAME model), Markov chain Monte Carlo (MCMC) methods, and reversible jump MCMC. Work done by the author in this area after publication of the first edition is also included. The author would like to thank Song Chun Zhu for valuable discussions and suggestions.

Preface to the First Edition

Since its beginning, image analysis research has been evolving from heuristic design of algorithms to systematic investigation of approaches. Researchers have realized: (1) The solution to a vision problem should be sought based on *optimization* principles, either explicitly or implicitly, and (2) *contextual constraints* are ultimately necessary for the understanding of visual information in images. Two questions follow: how to define an optimality criterion under contextual constraints and how to find its optimal solution.

Markov random field (MRF), a branch of probability theory, provides a foundation for the characterization of contextual constraints and the derivation of the probability distribution of interacting features. In conjunction with methods from decision and estimation theory, MRF theory provides a systematic approach for deriving optimality criteria such as those based on the *maximum a posteriori* (MAP) concept. This MAP-MRF framework enables us to systematically develop algorithms for a variety of vision problems using rational principles rather than ad hoc heuristics. For these reasons, there has been increasing interest in modeling computer vision problems using MRF's in recent years.

This book provides a coherent reference to theories, methodologies, and recent developments in solving computer vision problems based on MRF's, statistics, and optimization. It treats various problems in low- and high-level computational vision in a systematic and unified way within the MAP-MRF framework. The main issues of concern are how to use MRF's to encode contextual constraints that are indispensable to image understanding; how to derive the objective function, typically the posterior distribution, for the optimal solution to a problem; and how to design computational algorithms for finding the optimal solution.

As the first thorough reference on the subject, the book has four essential parts for solving image and vision analysis problems using MRF's: (1) introduction to fundamental theories, (2) formulations of various image models in the MAP-MRF framework, (3) parameter estimation, and (4) optimization methods.

Chapter 1 introduces the notion of visual labeling and describes important results in MRF theory for image modeling. A problem is formulated in terms of Bayes labeling of an MRF. Its optimal solution is then defined as the MAP configuration of the MRF. The role of optimization is discussed. These form the basis on which MAP-MRF models are formulated.

Chapter 2 formulates MRF models for low-level vision problems, such as image restoration, reconstruction, edge detection, texture, and optical flow. The systematic MAP-MRF approach for deriving the posterior distribution is illustrated step by step.

Chapter 3 addresses the issue of discontinuities in low-level vision. An important necessary condition is derived for any MRF prior potential function to be adaptive to discontinuities to avoid oversmoothing. This gives rise to the definition of a class of *adaptive interaction functions* and thereby a class of MRF models capable of dealing with discontinuities.

Chapter 4 provides a comparative study on discontinuity adaptive MRF priors and robust M-estimators based on the results obtained in Chapter 3. To tackle the problems associated with M-estimators, a method is presented to stabilize M-estimators w.r.t. the initialization and convergence.

Chapter 5 presents high-level MRF models for object recognition and pose determination. Relational measurements are incorporated into the energy function as high-level constraints. The concept of line process is extended for the separation of overlapping objects and the elimination of outlier features.

Chapter 6 describes various methods for both supervised and unsupervised parameter estimation, including the coding method, pseudo-likelihood, least squares method, and expectation maximization. A simultaneous image labeling and parameter estimation paradigm is also presented that enhances the low-level models in Chapter 2.

Chapter 7 presents a theory of parameter estimation for optimization-based object recognition. Two levels of criteria are proposed for the estimation: correctness and optimality. Optimal parameters are learned from examples using supervised learning methods. The theory is applied to parameter learning for the MRF recognition.

Chapters 8 and 9 present local and global methods, respectively, for energy optimization in finding MAP-MRF solutions. These include various algorithms for continuous, discrete, unconstrained, and constrained minimization as well as strategies for approximating global solutions.

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