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PREFACE

Image processing, electron optics, and electron detection are the subjects of this volume.

We begin with a chapter by A. Asif on noncausal random field models, which are attracting considerable attention in image and video processing but require a very different treatment from the models commonly found in the image processing textbooks. Asif explains in detail how these noncausal models are handled, and discusses three applications that illustrate the process.

This is followed by a particularly timely account by A.R. Faruqi of direct electron detectors for electron microscopy. With electron microscope image processing now commonplace, it was inevitable that new techniques for getting the electron image from the microscope to the computer would emerge. Faruqi describes two types of semiconductor pixel detectors in great technical detail and illustrates their usefulness in the area of electron cryomicroscopy. This new generation of detectors is of potential importance for a very wide audience, and I am delighted to include this survey here.

The third chapter is by Z.-x. Liu, who shows how useful MATHEMATICA can be for calculating expressions for the aberration coefficients of electron lenses. In the past, these coefficients have, for the most part, been established by hand at the expense of much long and dull algebra. For the higher-order aberrations, however, the task becomes gigantic and ever since the 1970s, the help of computer algebra has been invoked. Efficient and (reasonably) user-friendly commercial packages are now available, such as MAPLE and MATHEMATICA. Here, Liu shows how formula for the higher-degree chromatic aberrations of electron lenses can be established with the aid of Mathematica.

We conclude with a substantial contribution by D. Tschumperlé and R. Deriche on the role of anisotropic diffusion partial differential equations in the regularization of multichannel images. The authors examine the technique in considerable detail and give several examples, notably from the realm of color image processing.

As always, I thank all the authors for contributing to the series and for the trouble they have taken to make their material accessible to a wide readership. Forthcoming contributions are listed in the following pages.

Peter Hawkes

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DAVID TSCHUMPERLÉ AND RACHID DERICHE

Applications of Noncausal Gauss–Markov Random Field Models in Image and Video Processing

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I. Introduction

Noncausal Gauss–Markov random fields (GMRFs) have been used extensively in image processing. An analysis of the major applications reveals that GMRFs have been versatile enough to be applied in areas as diverse as stochastic relaxation for image restoration (Geman and Geman, 1984), surface reconstruction and pattern analysis (Geiger and Girosi, 1991), pattern recognition in computer vision (Rangarajan *et al.*, 1991), emission tomography in nuclear science (Lee *et al.*, 1993), textured image segmentation in image processing (Derlin and Elliott, 1987), anomaly detection in hyperspectral imagery (Schweizer and Moura, 2000), and data assimilation in physical oceanography (Asif and Moura, 1999). This chapter reviews the central concepts of noncausal GMRFs and explains these concepts by providing examples from the fields of image restoration, video compression, and matrix inversion in linear algebra.

Unlike the one-dimensional (1D) GMRF models, which naturally lead to recursive processing algorithms of the Kalman–Bucy type, the two-dimensional (2D) (Moura and Balram, 1992; Tekalp *et al.*, 1985; Woods, 1972) and three-dimensional (3D) (Schweizer and Moura, 2000) noncausal GMRFs are not conducive to recursion because of their bidirectional structure. After introducing the basic definitions, this chapter establishes several recursive one-sided formulations (Moura and Balram, 1992) for both 2D image field and 3D video sequences that are equivalent to the original noncausal GMRF models, yet enable the optimal recursive processing of the 2D and 3D fields. These recursive, one-sided formulations are obtained by performing a Cholesky factorization of the potential matrix $\mathcal{A}$, also referred to as the information matrix, which is the inverse of the covariance matrix $\mathcal{P}$. The forward Cholesky factorization, $\mathcal{A} = \mathcal{L}^T\mathcal{L}$, with $\mathcal{L}$ being a lower triangular matrix, leads to the forward unilateral representation that processes the 2D image field and the 3D video sequence in the natural order of occurence, i.e., starting with the first row ($i = 1$), all subsequent rows are processed one after the other in the lexicographic order ($1 \leqslant i \leqslant N_I$) from the first frame to the last frame.

This chapter highlights the central ideas of noncausal GMRFs by considering three applications. First, the classical image restoration problem is considered in which the input image is corrupted with additive noise and a convolutional blur resulting from such factors as sensor noise, improper image focus, and relative object-camera motion. The 2D forward unilateral model is used to develop a computationally efficient Rauch–Tung–Striebel (RTS) smoother-type algorithm, which, in comparison with the Wiener filter and filters that consider one-sided causal state models, restores blurred images at relatively higher peak signal to noise ratio (PSNR) and improved perceived quality. The second application of noncausal GMRFs is chosen from video compression in multimedia communications. The proposed video codec, referred to as SNP/VQR, models the 3D video sequence as a 3D noncausal GMRF that enables scalable, noncausal prediction (SNP) based on the 3D forward recursive representation. The resulting error field is compressed with vector quantization coupled with conditional replenishment (VQR). Because multimedia communications require real-time processing of video sequences, practical implementations of the SNP/VQR are derived by exploiting the block banded structure of the potential matrix $\mathcal{A}$ of the noncausal GMRF used to model the 3D video sequence. SNP/VQR outperforms the standard video codecs, including the MPEG4 and H.263, at low bit rates necessary for mobile wireless networks. Finally, a third application of noncausal GMRFs is selected from matrix inversion in linear algebra. In image and signal processing, it is often customary to invert large, block banded matrices. The theory of GMRFs is applied to develop computationally efficient algorithms for inverting positive definite and symmetric, L-block banded matrices $\mathcal{A}$ and their inverses $\mathcal{P}$. Compared to the direct inversion algorithms, the proposed algorithms provide computational savings of up to two orders of the magnitude of the linear dimension of the constituent blocks in $\mathcal{A}$ and $\mathcal{P}$.

This chapter is organized as follows. Section II, introduces terminology, as well as the basic definitions of the local neighborhoods, Markov, and Gaussian fields. The block banded structure of the potential matrices $\mathcal{A}$ along with the one-sided (unilateral) expressions representing the noncausal GMRFs for both 2D image fields and 3D video sequences are derived in Section III. Sections IV to VI consider the three applications of the noncausal GMRFs in the areas of image restoration (Section IV), video compression (Section V), and block banded matrix inversion (Section VI). For each application, we compare the performance of the GMRF-based algorithms with the standardized algorithms commonly used in these areas. Finally, Section VII concludes by summarizing the main concepts.

II. TERMINOLOGY

Before formally defining the GMRFs, we introduce the terminology used in the article. In our exposition, we follow much of the notation used in (Moura and Balram, 1992). Considering a still image as a 2D finite lattice of dimensions $(N_I \times N_J)$, the pixel intensity at site (i, j) is represented by the random variable $X(i, j)$. Lower-case letters $x_{i,j}$ denote the values assumed by $X(i, j)$. In other words, $x_{i,j}$ is a particular realization of the random variable $X(i, j)$. Similarly, a video sequence is modeled as a 3D lattice of dimensions $(N_I \times N_J \times N_K)$ with $X(i, j, k)$ representing the pixel intensity at spatial location (i, j) in frame k. As for still images, the lower-case letters $x_{i,j,k}$ denote the intensity value assumed by the 3D random variable $X(i, j, k)$. In terms of the pixel intensities, the conditional probabilities of the 2D and 3D Markov random fields are defined as follows.

2D Image Field:

$$\begin{aligned}&\text{Prob}\big(X(i,j) = x_{i,j} \mid X(m,n) = x_{m,n}, (i,j) \neq (m,n)\big)\\&\quad = \text{Prob}\big(X(i,j) = x_{i,j} \mid X(m,n) = x_{m,n}, (m,n) \in \mathcal{N}_{(p,2)}^{(m,n)}\big).\end{aligned} \tag{1}$$

3D Video Sequence:

$$\begin{aligned}&\text{Prob}\big(X(i,j,k) = x_{i,j,k} \mid X(m,n,q) = x_{m,n,q}, (i,j,k) \neq (m,n,q)\big)\\&\quad = \text{Prob}\big(X(i,j,k) = x_{i,j,k} \mid X(m,n,q) = x_{m,n,q}, (m,n,q) \in \mathcal{N}_{(p,3)}^{(m,n,q)}\big),\end{aligned} \tag{2}$$

where $\mathcal{N}_{(p,2)}^{(m,n)}$ is the pth-order neighborhood for spatial site (m, n) within the 2D image. Likewise, $\mathcal{N}_{(p,3)}^{(m,n,q)}$ is the pth-order local neighborhood for site (m, n, q) within the 3D video sequence. In keeping with the spirit of the Markovian property, the local neighborhoods are usually chosen to be of reduced order compared with the overall dimensions of the fields. Next, we define the neighborhoods on the basis of the Euclidean distance.

Local Neighborhoods: The pth-order neighborhoods are defined in terms of the closest neighbors of the reference pixel as follows.

2D Image Field: For 2D spatial coordinates (i, j),

$$\mathcal{N}_{(p,2)}^{(i,j)} = \big\{(m,n)\colon 0 < \big((m-i)^2 + (n-j)^2\big) \leqslant D_p\big\}. \tag{3}$$

3D Video Sequence: For 3D spatial coordinates (i, j, k),

$$\mathcal{N}_{(p,3)}^{(i,j,k)} = \big\{(m,n,q)\colon 0 < \big((m-i)^2 + (n-j)^2 + (q-k)^2\big) \leqslant D_p\big\}, \tag{4}$$

where D_p is an increasing function of order p that represents the square of the Euclidean distance between a pixel and its furthest neighbor. Figure 1 shows the 2D neighborhood configurations for pixel (i, j), represented by "o," with D_p set to 1, 2, 4, 5, 8, 9, corresponding to order $p = 1, 2, 3, 4, 5, 6$, respectively. Note that a neighborhood configuration of order p includes all pixels marked from "1" to "p." As an example, the second-order ($p = 2$) neighborhood is obtained by setting $D_p = 2$ and includes pixels labeled as 1s or 2s in Figure 1. In terms of the spatial coordinates (i, j) of the reference